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DEPARTMENT OF MOTOR VEHICLES

DEVELOPMENT AND EVALUATION OF A RISK MANAGEMENT STRATEGY FOR REDUCING CRASH RISK

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The goal of this project was to develop a strategy for maximizing the number of traffic crashes prevented by tailoring educational, rehabilitative, and license control interventions to identifiable high-risk problem driver groups.

Regression models were applied to a random sample of licensed California drivers with the objective of identifying groups of drivers with elevated risks of being involved in future traffic crashes. The driving records of the risk groups identified from the models were examined to identify drivers not receiving any form of driver improvement or license control actions. The risk levels of these identified "untreated" drivers were compared with negligent operators who have received licensing actions to determine how existing discretionary and mandatory actions correlate with traffic safety risk. The defining characteristics of high-risk drivers escaping driver improvement or license control actions were examined in an attempt to construct a recommended set of countermeasures. The potential utility of these countermeasures in terms of crash reduction and benefit-cost ratios was estimated based on prior research evidence and mathematical simulation.

In examining the defining characteristics of high-risk groups that currently escape driver improvement interventions, the majority was characterized either by TVS dismissals, citations, or crashes. These elements often combine with each other and with other risk factors to increase crash risk beyond that of drivers who meet the state's *prima facie* definition of a "negligent operator."

It is noted that there are two fundamental considerations for constructing a countermeasure system: (1) the countermeasures must be economically and operationally feasible, and (2) they must be legally permissible. Therefore, this study recommends interventions involving minimal expense, no in-person contact with DMV personnel, and no license-control actions.

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PREFACE

This project is part of the California Traffic Safety Program and was made possible through the support of the California Office of Traffic Safety, State of California, and the National Highway Traffic Safety Administration. The report was prepared by the Research and Development Branch of the California Department of Motor Vehicles. The opinions, findings, and conclusions expressed in this publication are those of the authors and not necessarily those of the State of California or the National Highway Traffic Safety Administration.

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EXECUTIVE SUMMARY

Problem Identification

The ultimate objective of a traffic safety program is to reduce the number of fatal, personal injury, and property damage crashes. The traffic safety programs or countermeasures may function as a general or specific deterrent to crash involvement. Specific deterrent programs are directed toward certain predefined target groups and include measures such as alcohol abuse programs, traffic violator schools (TVS), or some form of postlicensing controls. The existence of such programs may also have some effect on the general driving population, operating as a general deterrent.

The optimum control and reduction of driver crash risk by a driver licensing agency involves several interrelated processes:

- Establish risk thresholds – what degree of crash risk is "acceptable" and at what point should the department intervene to reduce the crash rate of a group of drivers?

- Risk assessment – what are the crash rates of identifiable groups comprising the driving population? What types of drivers and driver characteristics are most likely to be associated with or predictive of subsequent crash involvement?

- Determine countermeasure effectiveness – what kinds of programs and countermeasures are most effective in reducing the crash-involvement rates for the

various high-risk drivers (i.e., what treatments are the most effective for which types of drivers)?

- System management – how should the department deliver, control, and monitor the application of the countermeasures so that the net benefits are maximized (i.e., how should the department's budgeted resources be allocated to maximize the number of crashes prevented)?

In essence, the maximum safety value of a crash countermeasure or intervention is a product of three parameters: (1) the crash risk level of the target group, (2) the volume of drivers affected, and (3) the effectiveness of the countermeasure. The net number of crashes prevented by a system of countermeasures is achieved by applying effective sanctions to drivers representing the highest crash risk.

The development and execution of the above model requires a driver record database for identifying high-risk drivers and delivering the appropriate countermeasure.

Using a departmental database containing longitudinal histories on 1% of all California drivers from 1964-98, this study employed multivariate statistical techniques and mathematical optimization models to identify those groups of drivers representing the highest risk of future crash involvement and to develop a set of countermeasures designed to achieve a maximum reduction in the annual number of crashes within existing budgetary resources. The achievement of this objective offers potential for the department to increase considerably the number of crashes prevented through driver licensing and postlicense control programs and to substantially increase the ratio between program benefits and costs.

Goal and Objectives

The primary goal of this project was to develop a strategy for maximizing the number of traffic crashes prevented by tailoring educational, rehabilitative, and license control interventions to identifiable high-risk problem driver groups. The goal was achieved by addressing the following objectives:

- To update the California Driver Record Study Database with 1992-98 statistical data.

- To conduct a statistical analysis and identify subgroups of problem drivers whose crash risk exceeds that of *prima-facie* negligent operators as defined by the department's current negligent operator treatment system, and possibly certain other risk-cutoff values.

- To develop new or select existing intervention strategies to use for high-risk drivers who currently are not subjected to any form of license control or rehabilitative actions.

- To develop a resource allocation model to guide program safety expenditures.

Methodology

The California Driver Record Study Database was used as the primary source for the data analyses. This database represents a 1% random sample (approximately 225,000 records) of California drivers. The database contains driver record data from 1964-98.

Multiple logistic regression was applied to the California Driver Record Study Database with the objective of identifying groups of drivers with elevated risks of being involved in future traffic crashes. The logistic regression procedures were used to evaluate models containing a set of predictors. Sensitivity and specificity curves and cross classification risk tables were constructed for the logistic regression models to demonstrate the accuracy of risk prediction.

The driving records of the risk groups identified from the resulting logistic regression models were examined to identify drivers who have not received any form of driver improvement or license control actions. The risk levels of these identified "untreated" drivers were compared with negligent operators who have received licensing actions to determine how existing discretionary and mandatory actions correlate with traffic safety risk. The defining characteristics of high-risk drivers who are escaping driver improvement or license control actions were examined in an attempt to construct a recommended set of countermeasures. The potential utility of these countermeasures in terms of crash reduction and benefit-cost ratios were estimated based on prior research evidence and mathematical simulation.

Results

The findings of this study demonstrate that although none of the models performed well in predicting which individual drivers will become crash-involved, the models do identify and define groups of drivers who present substantially increased risks of having crashes during a subsequent 3-year time window. More importantly, the models have greater predictive power than the present negligent-operator point system, and they identify substantial numbers of high crash-risk drivers whose record shows no evidence of having received driver improvement or license control interventions. Some illustrative benefit-cost calculations indicated that even very inexpensive and marginally effective interventions, such as warning letters and informational brochures, offer substantial cost-effective crash reduction potential.

In examining the defining characteristics of high-risk groups that currently escape driver improvement interventions, the majority is characterized either by TVS dismissals, citations, or crashes. These elements often combine with each other and with other risk factors to increase crash risk beyond that of drivers who meet the state's *prima facie* definition of a "negligent operator."

Recommendations

It was noted that there are two fundamental considerations for constructing a countermeasure system: (1) the countermeasures must be economically and operationally feasible, and (2) they must be legally permissible. For these reasons, this study recommended considering interventions that involve minimal expense, no in-person contact with DMV personnel, and no license-control actions. With these constraints in mind, the following menu of interventions are offered for consideration:

- Crash triggered treatments – Any high-risk group characterized by two or more crashes would receive an educational brochure on crash avoidance combined with a self-study/self-test kit. Authority for intervening against drivers based on their crash history, irrespective of culpability, can be found in California Vehicle Code (CVC) Section 13800a.

- Traffic violator school triggered treatment – Offenders would be sent a customized soft warning letter upon the second TVS citation dismissal or any combination of TVS and other entries equaling three. For TVS and other entry combinations of four or more, a customized hard letter would be used. Authorization for initiating driver improvement actions against offenders based on a non-conviction citation (TVS) is contained in CVC Sections 13800(d), 12809(e), and 13359.

- Age-mediated risk group treatments – Offenders whose high-risk designation is partially attributed to youth (18-21 years of age) would receive a customized warning letter and informational brochure. Those whose high-risk is mediated by old age (70 years & older) would receive a home-study self-assessment kit. This recommendation is currently under an experimental evaluation by the department's Research and Development Branch.

- Other risk groups – Several of the high-risk groups were not characterized by either TVS or crash entries. In most cases, these "other" groups have multiple zero-point citations, that when combined with other entries, elevate their crash-risk to that of negligent operator status. Although it may be counterintuitive, the fact that "noncountable" traffic citations are predictive of increased crash risk has been documented in numerous California studies. Initiating punitive license control actions against offenders on the basis of noncountable citations would not be appropriate, but there is nothing that would prohibit use of advisory letters warning such drivers of crash risks and negative consequences of continued violations.

The above four strategies provide a general framework for linking each high-risk target group to a cost-effective and operationally feasible countermeasure and are consistent with the department's goal of enhanced public safety.

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INTRODUCTION

Background

Almost all motor vehicle departments use driver postlicensing control systems that assign penalty points to various traffic law violations and establish levels of point accumulation at which licensing actions are taken. However, many of these programs base the number of penalty points assigned to each infraction type on a qualitative assessment without any strong empirical foundation. In addition, a large body of scientific literature indicates that it is difficult to accurately identify future crash-involved drivers on the basis of their motor vehicle crash and traffic citation records alone, making it necessary to consider additional factors to improve prediction of crash involvement.

The primary objective of driver postlicensing point systems is to identify and initiate driver improvement or license control actions against drivers who are most likely to be involved in crashes. It is also commonly assumed that the existence of point systems serves as a general deterrent to negligent driving and to the accumulation of numerous traffic related citations.

In California, the Department of Motor Vehicles (DMV) uses a negligent-operator (neg-op) point system that operates as follows. Each conviction for a violation of a traffic law carries a certain number of neg-op points. For example, a cited driver has one point added to his driving record for conviction of a speeding violation and two points for a conviction of a major violation such as driving under the influence of alcohol or drugs. When the point count reaches specified levels, the driver is exposed to a "treatment." This treatment is usually a warning letter for the lowest specified neg-op point level but can be as severe as suspension or revocation of the driver license at the highest level of neg-op action.

Section 12810.5a of the California Vehicle Code (CVC) defines a *prima facie* negligent operator as any noncommercial Class C (generally passenger car) licensed driver whose driving record shows a violation point count of four or more points in 12 months, six or more points in 24 months, or eight or more points in 36 months. Other sections of the CVC (13800 and 14250) grant the department discretionary authority to take a variety of license control actions, including license suspension, against drivers who meet the CVC's definition of a negligent operator. Since the program is discretionary, the CVC (Section 13950) also requires that drivers be offered the opportunity for an administrative hearing pursuant to any actions proposed under the negligent-operator provisions. The point system for heavy-vehicle commercial drivers (Classes A and B) is different from that for Class C drivers as defined in CVC Section 12810.5b. An overview of the findings and program improvements of California's negligent operator treatment evaluation system from 1976 through 1995 is presented in a paper by Peck and Healey (1995).

In addition to the negligent-operator point system, the DMV utilizes a number of other driver safety interventions. For example, CVC Section 13800 authorizes the department to conduct a reexamination to determine if the department should take an action against an individual's driving privilege when the individual has been involved in three or more crashes or one fatal crash, regardless of fault, within 12 months from the date of the first crash. The objective of this reexamination is to make drivers aware of the importance of crash prevention and how past crashes could have been avoided.

There are currently two variants of the standard licensing program incorporating driver age. One is provisional (or graduated) licensing for novice drivers under the age of 18. The other is license renewal by mail.

The provisional licensing program for minors was initiated because of concern over the high crash rates of young novice drivers. After the necessary tests have been passed and a provisional license is granted, the department still monitors the teen's driving record and imposes early sanctions (in the form of post-licensing control measures) upon signs of a driving problem.

The current renewal by mail program offers two 5-year license extensions to clean-record drivers, so long as they are under the age of 70. Present driving record requirements of the program include not holding a probationary license and, within the 2 years preceding license expiration, showing no more than one traffic conviction or responsible crash, no license suspension, no failure to appear in court if cited or pay a fine if convicted, and no refusal to submit to an alcohol test. However, drivers aged 70 and above must renew in person even if their driving records are free of citations and crashes.

It is conceivable that the department could increase the crash reduction potential of its safety programs by developing and implementing additional methods of identifying and treating high-risk drivers. This optimistic view presupposes that these methods would be effective in identifying future high-risk drivers that would not be identified by the current neg-op point system. If this presumption were true, risk management strategies and driver improvement efforts that have been proven effective could be applied to groups of high-risk drivers with similar characteristics and driving problems.

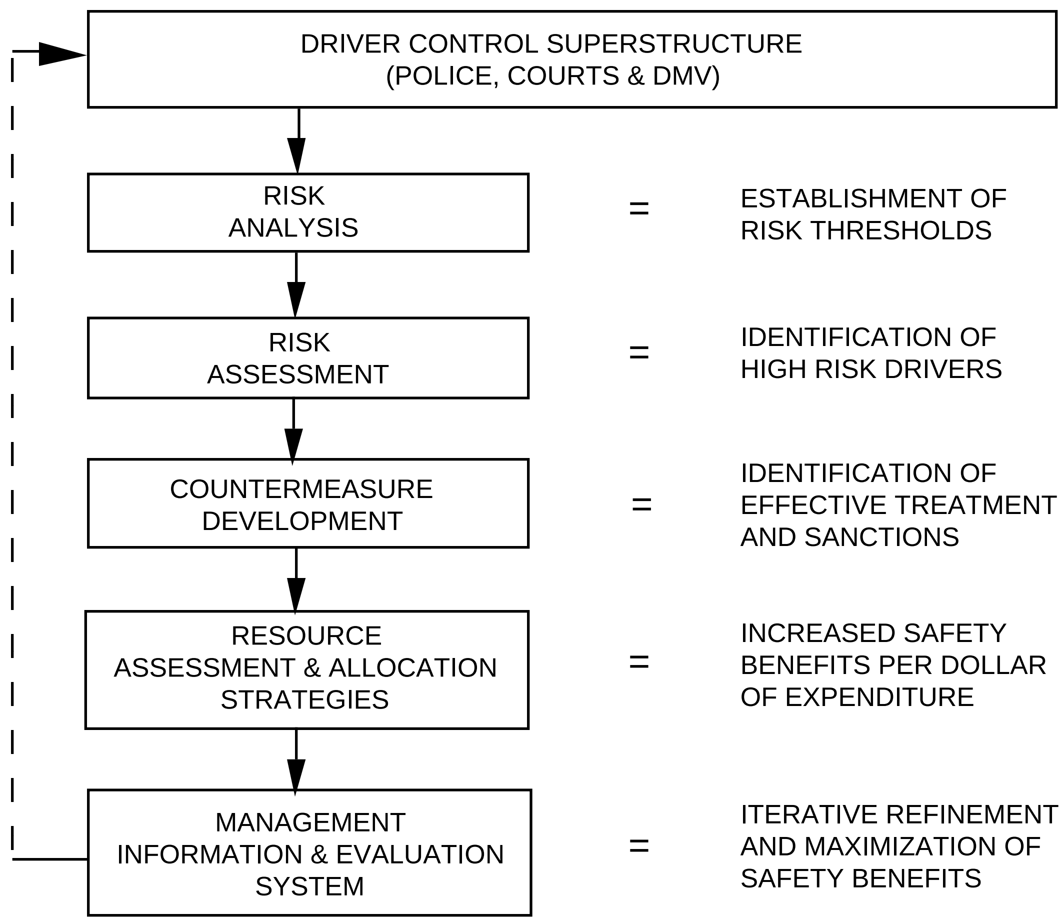
The ultimate objective of a traffic safety program is to reduce the number of fatal, personal injury, and property damage crashes. Traffic safety programs or countermeasures may function as a general or specific deterrent to crash involvement. Specific deterrent programs are directed toward certain predefined target groups and include measures such as alcohol abuse programs, traffic violator schools, or some form of postlicensing control. The existence of such programs may also have some positive influence on the general driving population by operating as a general deterrent.

The development of strategies for optimizing the safety benefits of a driver license system must proceed from an understanding of the transitory and stochastic nature of crash involvement rates. The vast majority or share (76.5%) of crashes in a given year in California involve drivers who have no crashes on their driving record during the preceding 2 years. Since the majority of crashes in a given year involve previously crash-free drivers, focusing countermeasures on just those who are involved in prior crashes will have little effect on the majority of subsequent crashes. Under these circumstances, crash countermeasures must be applied to a much larger percentage of the population if a substantive impact on crash rates is to be achieved. Strategies for broadening the population base to which safety-enhancements are applied have been proposed by several investigators, including Peck (1986).

Although accurate prediction of crash involvement for individual drivers would be the ideal situation for crash countermeasure development, the highly stochastic nature of crash occurrence makes this impossible. One must therefore be content with actuarial prediction—i.e. identifying factors that are associated with increased crash risk among groups of drivers who share common risk characteristics. Thus, we can identify groups of drivers who have substantially elevated crash risks relative to other drivers, but we cannot accurately predict which individuals in the group will be crash involved during any specific time period.

The majority of crash prediction studies conducted on California drivers have used predictor variables that are limited to data available in the department's automated Driver License Master File. This delimitation of predictor variables is appropriate since driver license agencies are constrained to make decisions based on available official file histories and related statutory considerations. Although this constraint may attenuate the substantive theoretical impact of the study findings, the impact of omitted variables is not as great as one might think. The most obvious omissions are data on exposure (miles driven) and socioeconomic status for individual drivers. However, these variables have been found to have a surprisingly modest impact in increasing R^2 beyond what is achievable with driver record variables alone (Peck, 1993; Peck & Kuan, 1983).

Despite the above limitations, the identification of high-risk driver groups is an important component of any process or system designed to reduce crash risk. Risk assessment is best viewed in the larger context of risk management as displayed in Figure 1.



Note. From Peck, R.C. (1986, Spring). The role of research and evaluation in a driver's licensing agency, *Research Notes*, pp. 1, 9.

Figure 1. A risk-management model of driver control.

Summarized below is a brief description of the four components of the risk management model as they relate to driver licensing agencies.

1. **Risk threshold determinations** – What degree of crash involvement risk is "acceptable"—i.e., at what point should a licensing agency intervene to reduce the crash rate of a group of drivers?

2. **Risk assessment** – What are the crash involvement rates of identifiable subgroups comprising the driving population? What types of drivers and driver characteristics are most likely to be associated with, or predictive of, subsequent crash involvement?

3. **Countermeasure effectiveness** – What kinds of programs and countermeasures are most effective in reducing crash involvements among the various high-risk drivers —i.e., what countermeasures are most effective for what types of drivers?

4. **System management** – How does the department deliver, control, and monitor the application of the countermeasures so that the net benefits are maximized—i.e., how does the department allocate its fixed budgetary resources to maximize the number of traffic crashes prevented?

The components that relate most directly to target group identification are risk assessment and countermeasure development. It is therefore instructive to consider in more detail the factors that influence decisions regarding the identification of high-risk target groups.

As illustrated in Figure 2, the net crash savings potential of a driver-oriented countermeasure is a function of the following three parameters:

1. Crash risk level of the target group (i.e., mean crash rate per driver);

2. size of the target population; and

3. effectiveness of the countermeasure.

These three attributes interact multiplicatively to influence the number of crashes prevented by a countermeasure. Figure 2 illustrates this with three examples (A, B, and C).

	Risk Level of Target Group		Size of Target Group		Effectiveness of Counter-measure		Number of Crashes Prevented
		X		X		=	
Example A	.50	X	10,000	X	50%	=	2,500
Example B	.30	X	100,000	X	20%	=	6,000
Example C	.50	X	100,000	X	50%	=	25,000

Figure 2. Parameters influencing the net impact of a traffic safety program or sanction policy.

Although this illustration may be obvious to many readers, there are a couple of implications that warrant comment. First, the size of the target population is of fundamental importance in determining the net impact of the program. Secondly, the crash risk level, although relevant, has less influence than does population size because the range and variance in the expected crash rates for different groups of drivers are attenuated by the relative infrequency of reportable crashes and by the large stochastic (chance) components that influence the actual occurrence of a crash.

The final component of the risk management model concerns resource allocation. Since the money and other resources available to manage crash risk are not infinite, one is inevitably faced with trade-offs and decisions on how to allocate finite budgeted resources in a way that maximizes the number of crashes prevented or some function of prevented crashes, such as net dollar benefits. Such an objective requires that any equation consider the cost of the program and the number of drivers that would be impacted. The following table presents hypothetical data to illustrate this point.

Table 1

Comparable Program Costs and Crash Savings Analysis

Example program (cost)	Cost per 100 treated drivers (a)	Crashes prevented per 100 treated drivers (b)	Number of drivers treated (c)	Total program cost (d)	Total crashes prevented (e)	Dollar value of crashes prevented (f)	Net dollar benefits (f-d)
A (inexpensive)	$100	1.0	2,000,000	$2,000,000	20,000	$360,000,000	$358,000,000
B (expensive)	$10,000	10.0	50,000	$5,000,000	5,000	$90,000,000	$85,000,000

Note. The dollar value of crashes prevented is based on a hypothetical average crash cost of $18,000 per crash. All other data in the table are hypothetical as well.

In Table 1, a relatively expensive program (program B) is compared to a very inexpensive program (program A). The inexpensive program might be something like a warning letter, and the expensive program might be an individual counseling session. Even if it is assumed that the expensive program were ten times more effective than the inexpensive program (column b), the table indicates that the inexpensive "weaker" program would be superior in terms of the "bottom line" indicators of total crashes prevented (column e) and net program dollar benefits (column f). The reason is that, in this example, the inexpensiveness of program A permits its use on a much larger volume of drivers (column c). Thus, the net impact and dollar benefits are substantially greater than would be achieved by applying the more expensive countermeasure to the much smaller volume of drivers. It should be emphasized again that these data are purely hypothetical. However, they serve to illustrate the need to consider both target group volume and countermeasure cost in determining how and where to allocate resources.

The above risk management model has direct parallels to the concepts of relative risk and population attributable risk used by epidemiologists in identifying and modifying risk factors in diseases such as cancer (Rothman & Greenland, 1998). On the assumption that the relative risk associated with a disease or risk factor represents a causal association, then the number of deaths or recurrences that are preventable if the risk factor were effectively removed can be estimated as a product of the relative risk and the number of individuals who have the risk factor. This risk parameter, which is known as the population attributable risk (PAR) or population attributable fraction (PAF), is frequently interpreted as a "theoretical ceiling" or "maximum potential epidemiological payoff." The population attributable risk is defined by the following formula:

$$\frac{b(r-1)}{b(r-1)+1}$$

where b is the proportion of the population with a particular risk factor (e.g., proportion of the driving population with two or more crashes in the prior 3 years) and r is the relative risk of a criterion event of interest (e.g., relative risk of subsequent crash involvement). For example, if a driver licensing agency removed all drivers with four or more traffic citations during the prior year, what proportion of traffic crashes would be prevented during the following year?

For illustrative purposes, assume that 1% of drivers have four or more traffic citations during a prior 1-year period and have a relative risk of traffic crashes during the subsequent year that is 5 times higher than the rate for drivers with no prior traffic citations. Then the population attributable risk is an observed relative risk of five minus the expected relative risk of one, all divided by the observed relative risk of five and then all multiplied by presence of the risk in the general driving population, .01, producing an index of 0.8%. In this example, although the relative risk of crash involvement is 5.0, the effect that drivers with four or more prior traffic citations have on the entire driving population is fairly small, 0.8% of all expected crashes. This is because relatively few drivers in the population are exposed to drivers with four or more traffic citations.

Considering the converse situation, in which exposure to a risk factor (e.g., drivers with a specified number of citations) confers only a small increased risk, the risk factor's commonness in the population is so great that it is associated with a substantial portion of traffic crashes. For example, assume that drivers with only one traffic citation in the prior year have about 1.5 times-as-many traffic crashes in the next year as do drivers with no prior traffic citations. However, assume that 50% of the driving population has one traffic citation during the prior year. This results in a population attributable risk of about 17%. In other words, removing drivers with only one traffic citation from the driving population would prevent 17% of the next year's traffic crashes, even though drivers with one traffic citation are only 1.5 times more likely to be involved in a future crash than are drivers with no traffic citations.

In contrast, removing drivers with four or more traffic citations would prevent 0.8% of the next year's traffic crashes, even though the four or more citation drivers are 5 times more likely to be involved in a future crash than zero-citation drivers.

<u>Resource and Countermeasure Allocation</u>
To identify and target high-risk driver groups, the following three items are needed:

1. A data record system for relevant risk entities (e.g., drivers, road types);
2. an algorithm for computing future crash-risk levels;
3. a delivery system for executing the appropriate countermeasure.

A general schematic of the process was illustrated by Peck (1992) and is reproduced below in Figure 3.

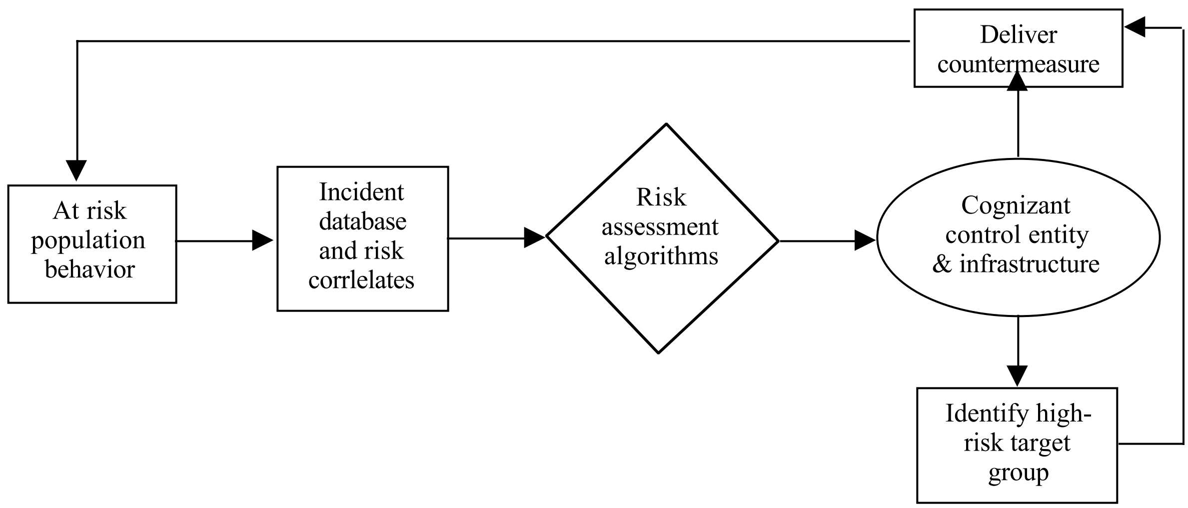


Figure 3. Simplified model of target group and countermeasure delivery system process.

It should be clear that very little can be done to reduce crash risk unless there exists an infrastructure for executing the process. It may be fairly simple to envision a plethora of risk factors and potential countermeasures and to construct and test epidemiological hypotheses; however, establishing an effective system of risk reduction is much more difficult. It is important that the existence (or feasibility) of the necessary delivery systems be explicitly considered in selecting priority target groups. It is also important that there be an infrastructure and database for estimating countermeasure and crash costs if formal benefit-cost and resource-allocation models are to be developed.

Figure 4 illustrates a model of four possible conditions that might apply to a driver selected to receive a traffic safety program treatment. Some drivers are implicitly or explicitly predicted to be crash-involved. These drivers may be those who accumulate a certain number of traffic citations or even the entire driving population. Some treatment is to be administered to these drivers. For example, the treatment might consist of a warning letter for drivers who accumulate a specific number of traffic conviction points or a public information campaign about DUI checkpoints during a holiday weekend. All of the benefits and costs will be restricted to drivers predicted to be crash-involved (i.e., those drivers in cells b and d who are defined as the predicted positives). The benefits are reduction in subsequent crashes, and these benefits depend on (1) the crash rate expressed as the mean crash rate per 100 drivers and/or the percentage of drivers who are crash-involved, (2) the size of the population being treated (the number of predicted positive drivers), and (3) the percentage reduction in crash involvement attributed to the treatment program. As stated earlier, the corresponding costs of the treatment depend on (1) the size of the population targeted for the treatment (number of predicted positives) and (2) the unit cost of the treatment.

Actual crash involvement	Predicted crash involvement	
	Crash free	Crash involved
Crash free	(a) True negatives (correct classification)	(b) False positives
Crash involved	(c) False negatives	(d) True positives (correct classification)

Figure 4. Model of crash involvement prediction classification.

Implicit within the benefit-cost strategy in traffic safety program design and decision-making is the assumption that the value of doing nothing is zero. That is, if there were no program, no benefits or added costs would exist. Since the crash countermeasures would be applied only to drivers predicted to be crash-involved (cells b and d in Figure 4), all of the resulting benefits and costs would be obtained from these drivers. Drivers predicted to be crash-free (cells a and c in Figure 4) would receive no treatment. The number of drivers that can be targeted for treatment depends on the cost of the program and on the available resources. All benefits obtained from applying a traffic safety program would be in the form of crash reduction; the costs would be the costs of administering the program.

High-Risk Target Groups

Over the past 30 years, DMV has conducted numerous studies to define the characteristics of high-risk drivers and to develop equations for predicting crash expectancies (Gebers, 1999; Harano, Peck & McBride, 1975; Harrington, 1972; McConnell & Hagen, 1980; Peck & Gebers, 1992; Peck & Kuan, 1983; Peck, McBride & Coppin, 1971). Similar studies have been conducted by other investigators (Burg, 1967; Campbell, 1958; Forbes, 1939). These studies have consistently reported that a driver's prior traffic conviction history is the single most accurate predictor of subsequent crash risk.

Results presented by Peck and Kuan (1983) are typical of the findings reported in the modeling of crash expectancies. These authors reported that all statistically significant driver record predictors available yielded a multiple correlation (R) of .204 but that prior citation frequency alone produced an R of .165. Therefore, this single variable (citations) accounted for 65% ($.165^2/.204^2$) of the total variance in crash frequency explained by all predictors combined. Peck and Kuan found that the equation containing all predictor sets, including a series of driver habits questionnaire variables, produced an R of .247. However, an equation containing only two variables, prior citation frequency and prior crash frequency, produced an R of .177.

It must be acknowledged that these R values are low, indicating very modest utility in predicting the subsequent crash involvement rate of *individual* drivers. However, as will be discussed in a latter section of this report, the level of prediction is sufficient to isolate groups of drivers whose crash expectancies are several times higher than that for the lowest risk group.

The above findings from Peck and Kuan (1983) represent relationships among driver record variables measured over a 6-year period (3 years prior/3 years post). Somewhat better prediction can be obtained by using longer driver-record intervals, since the use of a longer time window tends to increase the statistical reliability of the measures.

Peck and Gebers (1992) presented the results of a series of regression analyses that utilized several criterion measures in addition to total crashes (e.g., fatal and injury crashes, had-been-drinking [HBD] crashes, and total citations). In each case, the criterion and predictor intervals represented contiguous partitions of a 6- and 11-year time frame. The highest *R*s were obtained from the prior 6-year by post 5-year time split, although the increases in the *R*s were modest. For example, the authors found that the number of moving traffic citations (primarily one-point safety-related citations) alone accounted for the vast majority (77%) of the total explained variance. Adding total prior crashes increased R to .195 or 81% of the predictable crash variance. Peck and Gebers reported that information regarding individual violation types, including major violations, contributed very little additional precision to predicting crash risk.

The above authors also demonstrated that prior crash frequency actually made the largest unique or direct predictive contribution in several of the equations. The fact that the relative predictive accuracy of prior crashes—as compared to prior one-point citations—increases as the time window for the measurement lengthens is attributable to a differential enhancement in reliability. That is, traffic crash frequency, being generally smaller and more skewed than citation frequency, requires a longer time period to reach a certain level of statistical stability than does the corresponding citation measure.

In a more recent study, Gebers and Peck (in-press) used a canonical correlation approach to predict subsequent crash and citation frequencies simultaneously. They reported a 15% improvement in predictive accuracy over what could have been achieved from models keyed only to subsequent crash frequency.

McConnell and Hagen (1980) defined and validated a method for identifying groups of high-risk drivers. Based on 3-year driver records, five high-risk groups were identified from a sample of over 250,000 licensed drivers. These high-risk groups included drivers with various combinations of major and minor traffic citations. For each of the five groups, a regression equation was derived to maximize the prediction of crash involvement in a subsequent 3-year period. These equations were then cross-validated on independent samples that met the risk-groups' definitions. The drivers identified as being high-risk by this approach were compared to drivers identified as being high-risk using two alternative regression equations and the neg-op point approach. While the high-risk group approach proved more effective than the neg-op point approach in predicting future crashes, the regression equations using the weighted sum of all citations and all crashes were even more effective as crash prediction models. Based on these findings, the authors recommended implementation of a regression equation model using weighted crash and conviction data as the optimal system for selecting high-risk drivers for postlicensing control actions.

Additional confirmation of crash prediction modeling results from California data can be found in three Canadian driver record studies (Boyer, Dionne & Vanasse, 1990; Chen, Cooper, & Pinali, 1995; Hauer, Persaud, Smiley & Duncan, 1991). Each Canadian study reported statistically significant associations between increased subsequent crash frequency and increasing numbers of citations and crashes in the previous period using multiple regression techniques. However, two of the studies (Chen, et al., & Hauer, et al.) differed somewhat from the California findings in showing that prior crashes were somewhat better predictors than were prior citations. In the case of Chen et al., this difference could be due to the fact that their study was confined to at-fault crashes in both the prior and post periods. The limitation in using only at-fault crashes was demonstrated by Hauer et al.; they used both at-fault crashes and total crashes as predictors and found total crashes to be far superior to at-fault crashes and also to total citations.

The existence of regional (state) variations in the relative importance of crash predictors is not surprising since the distributional characteristics and reliability of traffic citation and crash frequencies are sensitive to state reporting policies and enforcement levels.

The role of alcohol impairment as a major causal factor in crashes, particularly in fatal crashes, has been established. However, until Peck and Helander (1999) examined the issue, the extent to which crash risk varies as a function of the number of driving-under-the-influence (DUI) offenses on a driver's record was less clear. The following two tables and findings are reproduced from Peck and Helander (1999).

Table 2 displays the relationship between the number of major violations (i.e., DUI, hit-and-run, and reckless driving) on a driver's record over a 3-year period and crash involvements in the prior 5-year period. As expected, the crash frequency increases monotonically with increases in the number of DUI-related convictions. Drivers with two or more major violations have almost 2.5 times as many crashes as do drivers with zero major violations. In interpreting these rates, it is important to keep in mind that the crash rates have been accumulated in the period *prior* to the counts of major convictions.

Table 2

Rate of Prior Total Accidents in 1984-88 by Number of Major Citations in the Subsequent 3-Year Period (1989-91)

Subsequent major citations (1989-91)	Number of drivers	Mean prior total accidents (1984-88)	Relative risk index (1984-88)*	% prior accident-free drivers (1984-88)
0	136,146	0.265	1.00	78.28
1	2,860	0.468	1.77	65.07
2+	479	0.649	2.45	55.74

Note. Pearson correlation = .063 ($p < .01$).
*Represents the relative increase in each group's total accident rate compared to the zero group's total accident rate.

Table 3 illustrates a reversal of the temporal relationship displayed in Table 2. Table 3 depicts the relationship between the number of DUI-related convictions in a 5-year period and crash involvements in the subsequent 3-year period. The risk gradient in Table 3 is much flatter than the risk gradient in Table 2, and the relationship displayed in Table 3 is no longer monotonic. Note that the crash rate for repeat offenders is actually lower than that for first-offenders, and their relative risk of 1.08 indicates only a slightly greater risk (8% higher) compared to the risk in the general driving population.

Table 3

Rate of Subsequent Accidents in 1989-91 by Number of Major Citations in the Prior 5-Year Period (1984-88)

Prior major citations (1984-88)	Number of drivers	Mean subsequent total accidents (1989-91)	Relative risk index (1989-91)*	% subsequent accident-free drivers (1989-91)
0	134,531	0.146	1.00	87.15
1	4,119	0.187	1.28	83.95
2+	835	0.158	1.08	86.23

Note. Pearson correlation = .013 ($p < .01$)
*Represents the relative increase in each group's subsequent accident rate compared to the zero group's subsequent accident rate.

As Peck and Helander (1999) pointed out, this seeming paradox (the lower crash rate for repeat offenders) becomes readily explainable when one realizes that the period for accumulating counts is a 3-year period directly following the DUI convictions, which would be attenuated by the effects of the sanctions and license control actions emanating from the convictions. The authors stated that, in a sense, the crash rates prior to the DUI convictions represent the intrinsic risk of DUI offenders while the subsequent rates represent the residual risk after sanctions have been applied. In California and in many states, repeat offenders are subject to more severe court sanctions, longer license control actions, and more intensive alcohol treatment program requirements than are first offenders.

The question arises as to which set of risks (prior or subsequent crash rate) is more relevant in formulating policy and identifying research needs. Peck and Helander (1999) concluded that the answer depends on the question being asked, but a strong case could be made for use of subsequent crash and reoffense risks in developing offender countermeasures.

One of the reasons for the general predictive superiority of total moving violations over total crashes and major violations is their greater frequency and range of variation. The very small proportion of drivers with more than two crashes or two major violations attenuates any intrinsic relationship these factors have with subsequent crash propensity, thereby reducing their utility for identifying high-risk target groups.

As stated earlier, Peck and Gebers (1992) summarized the results of a series of multiple regression analyses utilizing several driver record variables as dependent criterion variables, including traffic citations. Total traffic citation frequency, which consists primarily of one-point moving violations, was by far the most predictable measure, in one case yielding an *R* of .551. The multiple regression equation indicated that the great majority of the predictive accuracy was attributable to the sample's prior total conviction frequency. In contrast, traffic crash frequency was much less predictable, yielding multiple *R*s ranging from .168 to .216. These findings are consistent with those of numerous investigators.

The preceding results suggest that some combination of traffic conviction and crash frequencies might be useful in identifying high-risk groups. California's negligent-operator point system essentially incorporates this concept.[1] Gebers and Peck (1994) reported how relative crash risk increases as a function of the number of neg-op points in the prior 3 years. It was illustrated that drivers with eight or more points, who meet California's *prima facie* definition of a negligent operator and consequently can receive a variety of license control actions, had 3.74 times as many crashes as did drivers with zero points. More recently, Gebers & Peck (in press) used a canonical regression procedure to demonstrate that a regression function keyed to subsequent traffic violations and crashes jointly (a vector) resulted in a significant improvement in crash prediction accuracy.

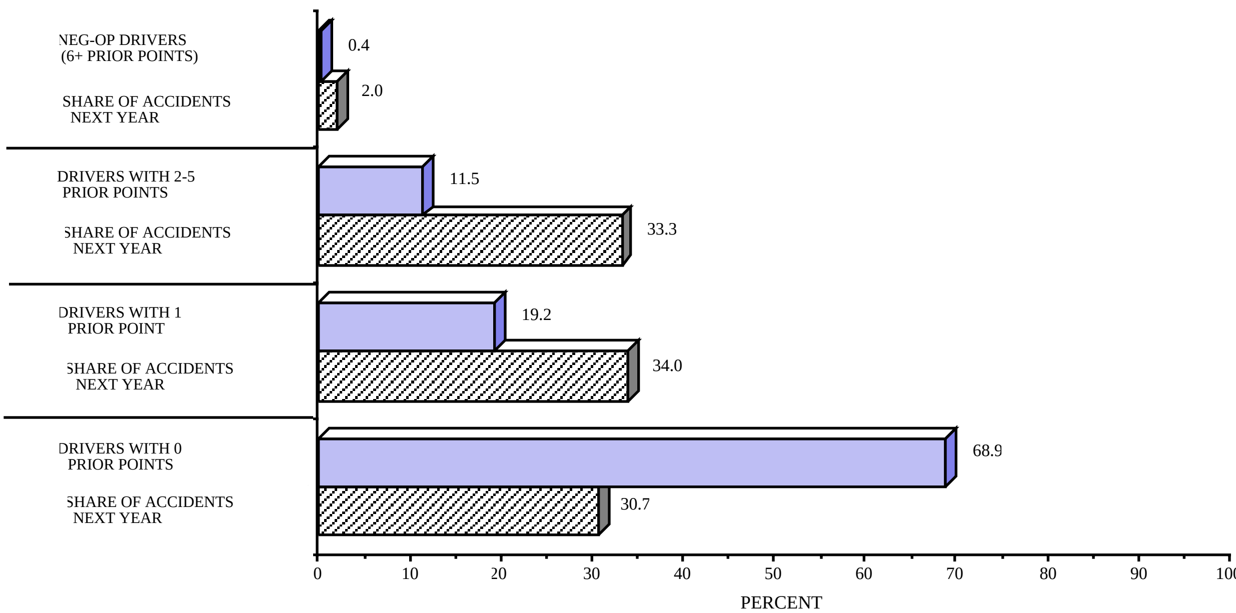


Figure 5. Percentage share of accidents during 1987 by negligent-operator points in the prior 2 years (1985-86).

[1] California's negligent-operator point system assigns one point to non-major moving violation convictions, two points to major violation convictions, and one point to responsible or culpable crashes.

A question that naturally arises from these crash-risk relativities is how many crashes could be prevented by a perfect countermeasure directed at high-point drivers? This question was addressed by Gebers (1990), who displayed in a figure the crash shares in 1 year involving drivers with given numbers of points in the prior 2 years. That figure is reproduced below.

It can be seen in the figure that drivers with six or more points in 2 years represent 0.4% of all drivers, but are involved in 2.0% of the subsequent year's crashes. This represents a five-fold (2.0/0.4) over-involvement. At two or more points in 2 years, about 12% of the population would have been targeted to potentially impact 35.3% of all traffic crashes.[2]

The results cited above illustrate both the strengths and limitations of targeting drivers based on prior driver record. Clearly, violation and crash repeaters represent high-risk drivers, and any countermeasure that could somehow render them "crash proof" would represent a major contribution to safety. However, the idea of even remotely approaching 100% effectiveness is not achievable, and we are also faced with the fact that the majority of the high-point drivers will be crash-free during a given year. Nevertheless, the risk differentials produced by using accumulated points is greater than what can be achieved with any other person-oriented variable, including drunk-driving convictions.

One could slightly improve predictive accuracy by including other predictors in the risk equations, using either additive (main effect terms only) or non-additive (interaction terms and/or polynomial terms) prediction models. An example of the latter was explored by Gebers and Peck (1992), who found that the risk gradients between points and crashes were not the same across age. The authors found that elevated point counts were predictive of a steeper increase in crash risk for drivers of advanced age than for drivers in general. One of the implications of this finding is that interventions should arguably be triggered earlier for drivers over 65 or 70 years of age. Under California's graduated licensing system, this is already done for drivers under 18 years of age.

Some additional accuracy in risk prediction can be achieved by taking into account citations that are dismissed pursuant to attending a certified traffic violator school (TVS). In California, about 25% of all court reported traffic citations are handled in this way (California Department of Motor Vehicles, 2002). However, because they do not constitute "convictions," these TVS referrals cannot be counted as points and used as a basis for DMV license control actions. The results of a California study indicated that TVS assignment is associated with a 10% increase in subsequent crash rate, compared to the rate that would be expected had the offender instead been convicted (Peck & Gebers, 1991). It is therefore instructive to explore how knowledge of a driver's TVS attendance history might increase the ability to identify high-risk target groups.

Gebers, Peck, Janke, and Hagge (1993) investigated the efficacy of using TVS dismissals along with neg-op points in selecting drivers for NOTS level 3 license control actions

[2] The techniques used to allocate the crash-involvement shares are described in Gebers (1990) and Gebers and Peck (1987).

(suspension with probation). The authors found that the crash expectancy for the additional drivers selected for level 3 actions when the TVS dismissals were added to the neg-op point count exceeded the average subsequent crash rate of NOTS level 3 drivers. For example, an option of adding all TVS dismissals to the incident or neg-op point count identified an additional 13,400 drivers eligible for level 3 actions (suspension with probation) and would have increased the 1989 volume of level 3 actions by 33%. Perhaps more importantly, the crash involvement rate for drivers identified under this option (15.75 per 100 drivers) was 21% higher than the involvement rate for NOTS level 3 drivers (12.99 per 100 drivers). Clearly, offenders attending traffic school continue to represent increased crash risk in the following year, and this information is relevant to identifying high-risk groups.

Countermeasure Development

California's negligent operator treatment system has been shown to have some utility in reducing the crash risk of negligent drivers (Peck & Healey, 1995). For example, in the department's last evaluation of the neg-op treatment system, it was reported that treatment levels 1 (warning letter), 2 (notice of intent to suspend), and 3 (suspension and probation) reduced subsequent crash involvement by 4.4%, 0.8%, and 11.6%, respectively (Marsh & Healey, 1995). However, the combined impact of these treatments is relatively modest, resulting in about 2,800 crashes prevented per year. One of the factors limiting the system's effectiveness is the low level of enforcement and prosecution of license suspension violations (DeYoung, 1990). The development of more effective methods of delivering and enforcing license suspensions could dramatically increase the general and specific deterrent effects of negligent driver control systems. For example, subsequent research by DeYoung (1998) reported that impounding vehicles for drivers cited for driving with a suspended/revoked license was linked to demonstrable traffic safety benefits; however, merely the threat of impounding/forfeiting vehicles was not sufficient to deter the general population of suspended/revoked drivers from driving and becoming involved in crashes.

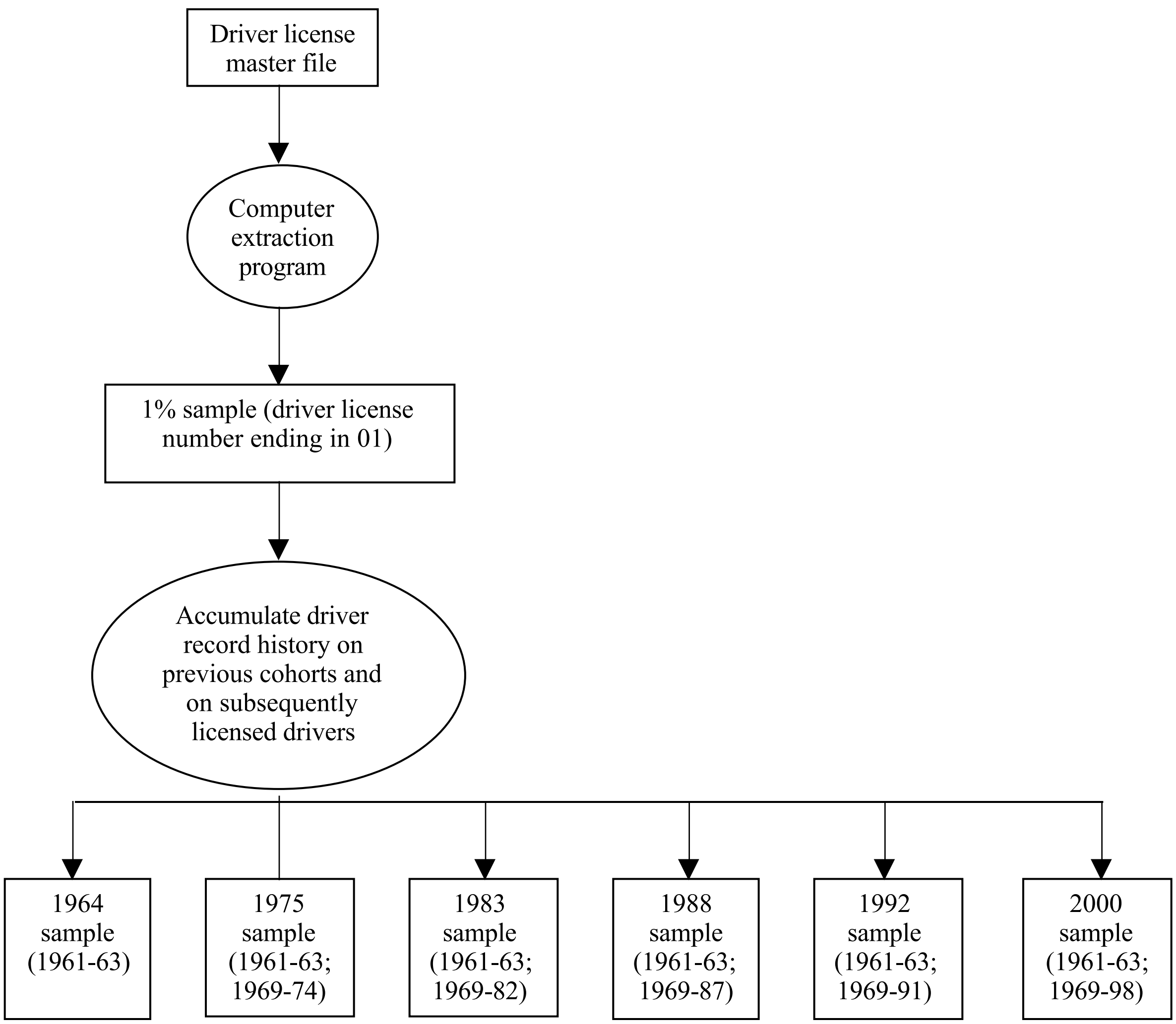
The net effectiveness of any countermeasure based on traffic conviction or crash frequency will also be impacted by certain ancillary factors, such as the amount and quality of the data used to trigger interventions. All things being equal, the accuracy of estimating risk levels and the net impact of countermeasures will increase as a function of the extent to which traffic citations and crashes that occur actually get reported to DMV. The amount and quality of traffic enforcement and crash investigation in many states are very poor, resulting in low volumes of traffic violations and crashes being reported (Insurance Research Council, 1991). Research and funding directed at improving state driver record files is needed to improve the crash-reduction effects of interventions delivered on the basis of point systems.

SAMPLING METHODOLOGY

The DMV maintains an automated computer file containing driving records for over 20 million California drivers. The driver license (DL) number for each record consists of a letter prefix followed by a seven-digit numerical field. A 1% random sample of driver records, consisting of those with a DL number ending in 01, was extracted from the department's master file during May 2000 and merged into what is called the California

Driver Record Study Database. This database provided the data used for the present study.

Figure 6 summarizes the structure of the California Driver Record Study Database. As illustrated in the figure, a 1% random sample of the DL Master File has been extracted six times in the past, beginning with a 1964 sample. Driver record history data obtained from each extraction were merged, based on a matching of DL numbers, with data previously extracted for existing cohorts. In addition, all drivers in the sample who were not captured in the previous extractions entered the database and formed the basis for future tracking.



Note. The time periods in parentheses represent the years for which driver record histories are available in the database. Due to a purge of data from the department's DL master file, there are no data for 1964-68.

Figure 6. Process for creating the California Driver Record Study Database.

Data for the approximately 250,000 driver records extracted in year 2000 include almost everything available on the DL file—demographic data, crashes and citations by type, physical and mental (P&M) condition codes, license suspension/revocation (S/R) actions, and license-status variables such as class of license and driving restrictions. Driver record information stored on the California Driver Record Study Database covers the period 1961 through 1963 and 1969 through 1998. Data for 1964 through 1968 were inadvertently purged from the DL file before they could be extracted and therefore are not included in the database. The time period covered by an individual driver record is a function of when the driver was first licensed in California. To be included in the sample, individuals had to possess a valid California driver license at the time of the extraction. All drivers with a "deceased" indicator on their record or whose driver license had been expired for more than 12 months at the time of the extraction were excluded. The final study sample included approximately 178,244 drivers.

The data available for processing and analysis in the study are listed below:

1. Driver identification data—driver license number, county of residence, date of birth, and gender.

2. Driver license process data—year of license issuance, type of license issuance (e.g., new, renewal, duplicate, name change), test results, license class (e.g., noncommercial, commercial), type of license restrictions, year of expiration, months license was expired, months license was in force, and physical and mental conditions affecting safe driving ability.

3. Driver record citation data—total number of reported traffic citations each year from 1993-98. This includes summaries of one-point, two-point, and zero-point (noncountable) citations.

   The total citations variable includes counts of convictions, failures to appear in court (FTAs), and traffic violator school (TVS) dismissals in the defined time period (based on violation date). Each citation incident is counted as only one conviction, one FTA, or one TVS dismissal, even if there are multiple violations (e.g., when a driver is cited for speeding and failing to stop for a red light on one "ticket"). The total citation variable is also disaggregated for the purpose of analysis into zero-point (non-countable) citations, one-point (non-major, safety-related-moving-violation) citations, and two-point (major) citations.

4. Traffic crash data—collected from 1993 through 1998. The data are presented for reported crashes only. California Vehicle Code Section 16000 requires the driver of each motor vehicle involved in a crash resulting in damage to the property of any one person in excess of $500, or in bodily injury or death of any person, to submit a written report to DMV. Failure to file a report under the above conditions will result in the suspension of the driving privilege. Information was also collected on the responsibility or culpability of the crash as obtained from any crash report filed by a law enforcement agency. A crash was categorized as an "at fault" crash if the official crash report showed the involved driver to be the party most at fault or a party who contributed to the cause of the crash. All reported crashes were investigated in this study.

5. Negligent-operator points—in determining neg-op points in California, one point is entered on the driving record for each moving-violation conviction (e.g., speeding, unsafe turns), except those involving "major" offenses such as driving under the influence of alcohol/drugs, reckless driving, and hit-and-run. The latter citations count two points each. A crash for which the driver is deemed at least partly responsible counts one point. As defined by CVC section 12810.5, drivers with a Class C driver license are defined as *prima facie* neg-ops when their driver records contain four or more points in 12 months, six or more points in 24 months, and eight or more points in 36 months.

6. Traffic violator school (TVS) dismissals—traffic citations that were dismissed contingent upon completion of a state-certified TVS program as defined in CVC Section 42005. A citation that is dismissed conditional upon the offender's completion of TVS does not have the legal status of a conviction. In other words, TVS dismissals represent traffic citations that would not be counted if the analyses were limited to abstracts of traffic convictions. Since TVS dismissals are proven correlates of crash risk and are associated with one-point citations, the count of TVS dismissals are (unless otherwise noted) included in the count of total and one-point citation variables reported in this paper. The count of TVS dismissals is not, however, included in counts of neg-op points or in the zero- or two-point citation variables reported in this paper.

7. Uncleared FTAs—the number of uncleared failure-to-appear violations. These are violations under CVC Sections 40002 and 40508, which refer to citations for traffic violations in which the driver failed to keep their signed promise to appear in court.

STATISTICAL ANALYSES

<u>Objective</u>

A full understanding of the statistical analyses requires a consideration of the primary objectives of this study. As stated in the Introduction section, the project consists of three main objectives:

1. To identify groups of problem drivers whose crash risk exceeds acceptable thresholds;

2. To develop intervention strategies for high-risk drivers who are currently not subjected to any form of license control or rehabilitative action; and

3. To develop a resource-allocation model to guide traffic safety program expenditures.

This section presents an overview of the statistical analyses and a description of the sequential steps used to accomplish these objectives. Some methodological details are reserved for the Results section because they are more understandable in the context of the findings.

Organization
The statistical analyses proceeded in the following sequence:

1. Examined biographical and driver record characteristics of California's general driving population;

2. Conducted a logistic regression main-effects model to assess the likelihood of subsequent crash involvement associated with prior counts of total citations, total crashes, TVS dismissals, and FTA violations;

3. Conducted a logistic regression main-effects model to assess the likelihood of subsequent crash involvement associated with prior counts of zero-point, one-point, and two-point citations, TVS dismissals, and FTA violations;

4. Conducted a logistic regression interaction-effects model to evaluate the moderating effects of driver age and counts of prior total crashes and prior total citations on the likelihood of subsequent crash involvement;

5. Applied the logistic regression crash prediction equations to obtain the following:
   - Plots of sensitivity and specificity curves;
   - Selection of various cutpoints and 2x2 prediction tables;
   - Comparison of cutpoint driving groups to existing groups of drivers receiving selected departmental license control actions;
   - Illustration of the effects of lowering and increasing expected crash thresholds;
   - Identification of high-risk driver groups currently escaping license control actions;

6. Development of a comprehensive countermeasure strategy and supporting rationale;

7. Illustration of the hypothesized impact on crash reduction; and

8. Development of resource allocation models and optimization.

The major computer software programs used for the data analyses were SAS Proc Freq, SAS Proc Corr, SAS Proc Logistic, SAS Proc Sort, and SAS Proc Tabulate (SAS Institute Inc., 1987; 1989a, 1989b).

Statistical Procedure
Multiple logistic regression was the statistical procedure used to develop and assess the prediction models. Since the model produced by logistic regression is nonlinear on the additive scale, the equations used to predict outcomes are slightly more complex than the more commonly used and familiar ordinary least squares regression equations. The interested reader is referred to texts such as Hosmer and Lemeshow (2000), Tabachnick and Fidell (2001), and Menard (1995) for a detailed discussion of logistic regression analysis. The criterion variable is the estimated probability of one outcome (i.e., crash involvement), based on a nonlinear function of the best linear combination of predictors. With just two possible outcomes (crash or no crash), the equation is

$$\hat{Y}_i = \frac{e^u}{1+e^u}$$

where $\hat{Y}_i$ is the estimated probability that the i[th] case (i = 1, …, n) is in one of the outcome categories (i.e., $Y = 1$) and u is a product from the linear regression model:

$$u = A + B_1X_1 + B_2X_2 + \ldots + B_kX_k$$

with constant A, coefficients B_j, and Predictors X_j for K predictors (j = 1, 2, . . ., K).

The quantity u may also be represented as the logit or natural log of the odds represented as:

$$u = \ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right) = A + \sum B_j X_{ij}$$

That is, the linear regression term is the natural log of the probability of having one outcome (crash) divided by the probability of having the other outcome (no crash). The procedure for estimating coefficients is maximum likelihood, and the goal is to find the best linear combination of predictors to maximize the likelihood of obtaining the observed outcome frequencies.

Use of a logistic regression model allows for the computation of the odds of crash involvement for one group relative to those odds for another group; that is, an odds ratio. For example, if the odds for males (coded 1) and the odds for females (coded 0) were compared, an odds-ratio greater than 1 would indicate that males are a higher crash risk. A value of 1 would indicate that both sexes have equal odds of being in a crash. An odds-ratio of less than 1 would indicate that males are a lower crash risk.

As introduced in steps 2 through 4 of the statistical analysis sequence described above, three logistic regression models were constructed and evaluated. The models chosen for the present study are based on variable combinations that in prior research evaluating crash prediction modeling for California's general driving population have resulted in the greatest degree of prediction and classification accuracy. (Gebers, 1998, 1999; Gebers, 1998; Peck & Kuan, 1983). Specifically, subsequent 3-year (1996-98) total crashes were regressed against the predictor variables in the following three models:

Model A

- Prior 3-year (1993-95) total citations
- Prior 3-year (1993-95) total crashes
- Prior 3-year (1993-95) TVS dismissals
- Prior 3-year (1993-95) FTA violations

Model B

- Prior 3-year (1993-95) zero-point citations
- Prior 3-year (1993-95) one-point citations
- Prior 3-year (1993-95) two-point citations

- Prior 3-year (1993-95) total crashes
- Prior 3-year (1993-95) TVS dismissals
- Prior 3-year (1993-95) FTA violations

Model C
- Prior 3-year (1993-95) total citations
- Prior 3-year (1993-95) total crashes
- Driver age
- Driver age by prior total citations interaction
- Driver age by prior total crashes interaction

Models A and B are referred to as *main effects* models. A main effects model is most typically defined as the constant effect of one variable across all values of another variable or set of variables.

Model C is referred to as an *interaction effects* model. An interaction effects model is a multiplicative model of the log odds (containing one or more terms representing the multiplication of one variable times another), and an interaction effect is said to exist when the effect of a predictor variable on a criterion variable differs depending on the value of a third variable called a moderator variable. For a detailed discussion of the differences between main effects and interaction effects regression models, the interested reader is referred to Aiken and West (1991) and Jaccard (2001).

One of the objectives of the present study was to examine the possibility of an interactive relationship between driver age and prior driving record as a method for identifying high-risk driver groups not currently subjected to any license control measures. Specifically, the results of the interaction regression model were used to assess whether young drivers (18-21 years of age) and older drivers (70 years of age and above) exhibit a steeper increase in future crash risk at successive prior incident levels relative to drivers in general. The existence of an interaction may justify customized driver safety programs tailored to driver age.

These *a priori* selected interactions were evaluated by forming the respective two-way product terms between age and prior total crashes and prior total citations. The statistical significance of the interactions was evaluated by the Wald chi-square and likelihood ratio tests (SAS, 1995; Hosmer & Lemshow, 2000; Jaccard, 2001). Where significant interactions existed, the structure of the interactions was summarized graphically by plotting the logits and relative risks from the regression coefficients for the respective main effect and interaction parameters.

Classification and Prediction Accuracy
Of critical importance for the use of the above noted regression equations in identifying high-risk driver groups for possible treatments and/or license control measures is the ability of the equations to correctly classify or discriminate between crash-involved and crash-free drivers.

The measures of importance in determining the discriminatory or classification accuracy of an equation are each model's sensitivity and specificity. Specificity is the proportion of no-event (i.e., crash-free) drivers that are correctly predicted to be no-event drivers.

Sensitivity is the proportion of crash-involved drivers that were correctly predicted to be crash-involved. For any given test or selection battery, the 2 errors are reciprocally related. Increasing the accuracy of a test in identifying future crash-involved drivers (sensitivity) also increases the number of crash-free drivers who will be predicted to have crashes (decreased specificity). Conversely, increasing the accuracy in predicting which drivers will be crash-free (specificity) decreases the accuracy of the test in identifying crash-involved drivers (decreased sensitivity). The only method of decreasing both errors simultaneously is to increase the predictive accuracy (discriminatory power) of the test.

As noted earlier, traffic crashes contain a large random or stochastic component, and any crash prediction equation will not be able to correctly identify an extremely high proportion of crash-involved drivers without also predicting a huge percentage of non-crash drivers to be accident involved. As a result, high specificity in combination with adequate sensitivity is the most critical requirement. If too many drivers are incorrectly identified as crash-involved (false-positive prediction errors) and subjected to some form of driver safety treatment, the treatment may become too expensive for the administrative agency to support and may inconvenience and generate complaints from the driving public. It is therefore inevitable that any operationally applied crash reduction model will not identify a substantial percentage of the crash-involved driving population.

Choice of a particular sensitivity-specificity tradeoff does not alter the logistic regression coefficients, significance levels, or the odds ratios of the predictor variables. The choice of the values does, however, alter the equations' classification accuracy in identifying the group (crash-free versus crash-involved) to which each individual is assigned.

In this study, the predictive performance of the models is illustrated by generating sensitivity and specificity plots for each model and by constructing a series of 2 x 2 tables to classify observed versus predicted outcomes at a variety of chosen cutoff scores. The actual cutoff scores used are defined and discussed in detail in the appropriate section of the Results.

Determining a Threshold for Treatment of Drivers and the Operational Implications

Following the assessment of the models sensitivity and specificity and computation of the sample's expected probability of subsequent crash involvement, an effort was made to identify high-risk drivers not currently subjected to any form of license control or rehabilitative action and then to determine what new or existing intervention strategies could be administered.

To accomplish this goal, it was necessary to establish crash-risk thresholds. In other words, it was necessary to determine what level of crash-involvement risk is acceptable and at what point the department should intervene to reduce the crash rate for a group of drivers.

Inherent in this approach is the assumption that developing and implementing additional methods of identifying and treating high-risk drivers can increase the crash-reduction potential of the department's traffic safety programs. The strategy used in the present study assumes that any group of drivers whose total crash expectancy (e.g., average crash rate or estimated probability of crash involvement) is approximately equal to or exceeds that of drivers treated by the Negligent-Operator Treatment System (NOTS), or that of drivers receiving one or more major violations, is a legitimate target group for licensing actions.

The selection of NOTS treated drivers and major violators to serve as the study's comparison groups was motivated by an attempt to include as the baseline drivers exposed to driver improvement interventions under different settings. As noted by Lonero, Clinton, Mayhew, Peck, Smiley, and Black (2002), the NOTS treatment system represents an administrative method of driver improvement. Administrative driver improvement is postlicensing control and is under the regulatory authority of driver licensing administration. Postlicensing control involves the monitoring, treatment, and sanctioning of drivers who have been convicted or have crashed repeatedly. Administrative driver improvement programs typically exclude drivers convicted of the most serious offenses. On the other hand, major violators are those drivers convicted of the most serious traffic offenses and are typically sanctioned directly through the court system and, in most cases, any license control actions are statutorily prescribed.

The current Negligent Operator Treatment System consists of four levels of intervention designed to treat and sanction individuals who accumulate neg-op points due to traffic convictions and/or traffic crashes for which they were responsible. License control actions are taken when the number of neg-op points accumulated over 1, 2, and 3 years reaches certain levels. The first two levels involve warning only. Drivers are classified as *prima facie* negligent operators when they accumulate sufficient points to reach one of the criteria for levels 3 (probation/suspension or 4 (probation violator). The four levels of action for License Classes 3/C and 4/M drivers (i.e., those other than heavy-vehicle operators) are:

1. Warning letters, sent to drivers who accrue:
   a) two points in 1 year, or
   b) four points in 2 years, or
   c) six points in 3 years

2. Notices of intent to suspend, sent to drivers who accrue:
   a) three points in 1 year, or
   b) five points in 2 years, or
   c) seven points in 3 years

3. Probation hearing, required for drivers who accrue:
   a) four or more points in 1 year, or
   b) six or more points in 2 years, or
   c) eight or more points in 3 years.

   Drivers attending a level 3 hearing normally receive a relatively brief (6-month) suspension as a condition of probation, although some drivers may receive only probation without suspension. Those failing to attend their scheduled hearing receive an automatic 6-month license suspension followed by a 1-year probation.

4. Probation-violator sanctions (suspension or revocation) are given to drivers who, during probation, accumulate any additional neg-op points or fail to appear in court or forfeit bail in connection with traffic citations. Penalties are a 30-, 60-, or 90-day license suspension for the first violation of probation, a 6-month suspension for the second or third violation, and revocation for the fourth violation.

Similarly, drivers receiving major two-point citations represent a group of high-risk drivers and receive a series of sanctions. Since the majority of major two-point citations are alcohol related, these drivers usually receive the severe sanctions (e.g., high court fines, suspended/revoked licenses, expensive treatment programs, restricted licenses) applied for DUI offenses.

All four NOTS treatments and treatments targeting major violators have been shown to be effective in preventing crashes (Peck & Healey, 1995; Peck & Helander, 1999). Any group of untreated drivers whose crash risk approximates or exceeds that of major violators or drivers treated by NOTS will have a negative impact on traffic safety. Therefore, in the following analyses, the traffic crash risk posed by drivers treated by the neg-op point system or receiving one or more major violations is used as the "risk" standard for determining the number of additional drivers identified for any proposed treatment or countermeasure strategies and resource allocation models originating from this study.

RESULTS

Total Crash Risk Regression Equations

Main effects models. Table 4 presents a summary of the nonconcurrent 6-year (1993-95; 1996-98) multiple logistic regression equation for predicting total crash involvement from Model A.

Table 4

Summary of Nonconcurrent 6-Year (1993-95; 1996-98) Multiple Logistic Regression Equation for Predicting Total Crash Involvement from Model A (n = 187,313)

Predictor variable	Regression coefficient	Standard error	Wald χ^2	p	Odds ratio	Odds ratio 95% confidence interval
Intercept	-2.0691	0.00836	61,288.07	< .001	NA	NA
Total citations	0.1733	0.00766	511.53	< .0001	1.19	1.17 – 1.21
Total crashes	0.3148	0.0145	472.77	< .0001	1.37	1.33 – 1.41
TVS dismissals	0.3936	0.0164	578.35	< .0001	1.48	1.44 – 1.53
FTA violations	0.0857	0.0168	25.92	< .0001	1.09	1.05 – 1.13

-2 log likelihood for intercept only = 146,937.26

-2 log likelihood for intercept and predictors = 144,938.71

χ^2 for predictors only = 1,998.55 , $p < .0001$, $R_{cs}^2 = .0106$

As detailed in Table 4, Model A consisted of a main-effects regression equation in which prior 3-year (1993-95) total citations, total crashes, TVS dismissals, and FTA violations were used to predict subsequent 3-year (1996-98) total crash involvement.

A test of the model against an intercept or constant-only model was statistically significant ($\chi^2 = 1{,}998.55$, $p < .0001$), indicating that the set of predictors reliably distinguished between crash-involved and crash-free drivers in the sample. The variance in crash involvement that is accounted for is small, however, with a Cox-Snell R^2_{cs} of only .0106.[3]

Table 4 also shows the regression coefficient, Wald test statistic, and odds ratio for each predictor. The Wald test is a simultaneous test for evaluating parameters in which the effect of each variable in the model is adjusted for the effects of all other included variables. A significant Wald χ^2 statistic was found for prior total citations, total crashes, TVS dismissals, and FTA violations, indicating that each of these four variables reliably predicted subsequent crash involvement. The signs and magnitudes of the parameter estimates indicate that subsequent involvement in a traffic crash is associated with the following:

- Increasing numbers of prior total citations. The odds ratio of 1.19 for total citations indicates that the odds of involvement in subsequent traffic crashes increase by a factor of approximately 1.19 (19%) as the count of prior 3-year total citations increases from 0 to 1 (or 1 to 2, 2 to 3, etc.).

- Increasing numbers of prior total crashes. The odds ratio of 1.37 for total crashes implies that the odds of involvement in a subsequent total crash increase by a factor of about 1.37 (37%) for every unit increase in the number of prior total crashes.

- Increasing numbers of prior traffic violator school dismissals. The odds ratio of 1.48 for TVS dismissals indicates that the odds of subsequent total crash involvement increase by a factor of about 1.48 (48%) for every unit increase in the number of prior TVS dismissals.

- Increasing numbers of prior FTA violations. The odds ratio of 1.09 associated with FTA violations implies that the odds of involvement in a subsequent traffic crash increases by a factor of 1.09 (9%) for every unit increase in the number of prior FTA violations.

Table 5 summarizes the nonconcurrent 6-year (1993-95; 1996-98) multiple logistic regression equation for predicting total crash involvement from Model B.

[3] The Cox-Snell R^2 is provided to the reader who is more familiar with ordinary least squares as an approximate measure of strength of association for the models evaluated in this study. See Menard (1995) and Tabachnick and Fidell (2001) for a discussion on strength of association measures available in logistic regression analyses.

Table 5

Summary of Nonconcurrent 6-Year (1993-95; 1996-98) Multiple Logistic Regression Equation for Predicting Total Crash Involvement from Model B
(n = 187,313)

Predictor variable	Regression coefficient	Standard error	Wald χ^2	p	Odds ratio	Odds ratio 95% confidence interval
Intercept	-2.0671	0.00835	61,292.99	< .0001	NA	NA
Zero-point citations	0.1711	0.0142	145.19	< .0001	1.19	1.15 – 1.22
One-point citations	0.2077	0.0104	400.61	< .0001	1.23	1.21 – 1.26
Two-point citations	0.1247	0.0415	9.02	< .0027	1.13	1.04 – 1.23
Total crashes	0.3200	0.0145	487.78	< .0001	1.38	1.34 – 1.42
TVS dismissals	0.3808	0.0165	533.64	< .0001	1.46	1.42 – 1.51
FTA violations	0.0807	0.0176	20.93	< .0001	1.08	1.05 – 1.12

-2 log likelihood for intercept only = 146,937.26
-2 log likelihood for intercept and predictors = 144,877.99
χ^2 for predictors only = 2059.26, $p < .0001$, $R_{cs}^2 = .0109$

In this model, the total citations variable has been disaggregated into its component parts consisting of zero-point, one-point, and two-point citations which are used as separate predictors. The three other predictors in the model are prior total crashes, TVS dismissals, and FTA violations.

A test of the full model against an intercept or constant-only model was statistically significant ($\chi^2 = 2{,}059.26$, $p < .0001$). The Cox-Snell R^2 value was again small, at .0109, indicating that the model accounted for a very small portion of the variance in crash involvement.

Results from the Wald tests for the individual variables presented in Table 5 indicate that each predictor was significantly associated with the crash outcome after adjustment for the effects of the other predictors in the model. The signs and magnitudes of the parameter estimates indicate that the odds of a subsequent crash involvement increased by:

- A factor of 1.19 (19%) with each unit increase in the number of prior zero-point citations.
- A factor of 1.23 (23%) with each unit increase in the number of prior one-point citations.
- A factor of 1.13 (13%) for every unit increase in the number of prior two-point citations.

- A factor of 1.38 (38%) for every unit increase in the number of prior total crashes.
- A factor of 1.46 (46%) for every unit increase in the number of prior TVS dismissals.
- A factor of 1.08 (8%) for every unit increase in the number of prior FTA violations.

Interaction effects model. As noted earlier, the methodology for this study included an evaluation of selected interactions between driver age and prior total citations and prior total crashes. The rationale for testing the presence of the selected interactions was to assess whether young drivers aged 18 through 21 or older drivers aged 70 or above exhibit a steeper increase in future crash risk at successive prior crash or prior citation levels as compared to drivers in general. The existence of one or more significant interactions could be used as evidence to justify developing customized traffic safety programs tailored to driver age.

Before discussing these results, some clarification is in order concerning the procedures used in constructing and evaluating the interaction models. Total citations and total crashes were entered into the equation as continuous variables along with the appropriate two-way age-by-citations and age-by-crashes product terms. To reduce multi-collinearity (i.e., statistical problems emanating from intercorrelations among independent variables), the total citations and total crash variables were first "centered" by subtracting the respective sample's citations and crash means from each subject's observed citations value and crash value.

The driver age variable is comprised of three categories even though the output shows only two categories. The two displayed categories are drivers aged 18 through 21 and drivers aged 70 and above. The deletion of one category (drivers aged 22 through 69), classified as the referent category, is required to prevent a singular matrix—i.e., a situation in which a variable or category is a perfect linear function of the other categories or covariates. No information is lost in doing this because the regression coefficient for each variable reflects the difference in the crash logit, or log of the odds, between the noted category and the referent group.

The reader will note from the above discussion that drivers under age 18 have been omitted. Since licensed California drivers under age 18 are already subjected to age-tailored license restrictions and postlicense controls under California's Graduated Licensing Program, these drivers have been excluded from the interaction model.

In formulating the interaction regression models, a modified backward elimination procedure was used in which the interactions were forced into the equation and then eliminated one at a time until a likelihood ratio test with a significant value of $p < .05$ was obtained. The goal of such modeling is to find the reduced model with the fewest effects that still closely mimics the observed value of the outcome variable.

Results of the backward elimination likelihood ratio tests comparing models with and without interactions indicate that the model consisting of both the age-by-citations interaction and the age-by-crashes interaction (i.e., Model C) was the model that most closely predicted or "mimicked" the observed values of the subsequent total crash criterion. Therefore, Model C is the model that will be explained in detail in the following discussion.

Table 6 presents a summary of the nonconcurrent 6-year (1993-95; 1996-98) multiple logistic regression equation for predicting subsequent total crash involvement from interaction Model C. The reader will note that the exclusion of drivers under age 18 resulted in a sample size (n = 186,258) that is slightly smaller than the sample size (n = 187,313) for Models A and B presented in Tables 4 and 5, each consisting of all licensed drivers aged 16 or older.

Table 6

Summary of Nonconcurrent 6-Year (1993-95; 1996-98) Multiple Logistic Regression Equation for Predicting Total Crash Involvement from Model C (n = 186,258)

Predictor variable	Regression coefficient	Standard error	Wald χ^2	p	Odds ratio	Odds ratio 95% confidence interval
Intercept	-1.9202	0.0075	65,945.55	< .0001	NA	NA
Total crashes	0.3336	0.0157	450.48	< .0001	1.40	1.35 - 1.44
Total citations	0.1807	0.0060	902.96	< .0001	1.20	1.18 - 1.21
Age (referent group: 22-69)			216.60	< .0001		
18-21	0.4115	0.0280	216.24	< .0001	1.51	1.43 - 1.59
70 & above	0.0514	0.0367	1.97	.1608	1.05	0.98 - 1.13
Age by prior total crashes			15.55	.0004		
Age 18-21 by prior total crashes	-0.1733	0.0478	13.14	.0003	0.841	0.77 - 0.92
Age 70 & above by prior total crashes	0.0850	0.0670	1.61	.2048	1.09	0.96 - 1.24
Age by prior total citations			52.07	< .0001		
Age 18-21 by prior total citations	-0.0673	0.0155	18.80	< .0001	0.935	0.91 - 0.96
Age 70 & above by prior total citations	0.3267	0.0584	31.25	< .0001	1.39	1.24 - 1.56

-2 log likelihood for intercept only = 145,829.87

-2 log likelihood for intercept and predictors = 143,798.23

χ^2 for predictors only = 2031.64, $p < .0001$, $R_{cs}^2 = .0108$

Although the existence of statistically significant interactions focuses attention on the interpretation of the interactions rather than on the main effect terms, the nature of regression requires that all lower-order-main-effect terms be included in the models containing corresponding higher-order-interaction terms. Specifically, as displayed in Table 6, Model C evaluates the contribution of a two-way interaction between driver age and prior total citations and a two-way interaction between driver age and prior total crashes. As displayed in the table, the existence of the two-way interactions requires the inclusion of all lower order age, total citations, and total crashes main effect terms.

While the full model containing the two two-way interactions and main effects is statistically significant ($\chi^2 = 2{,}031.64$, $p < .0001$), the question as to whether the existence of the various interactions reliably contributes to the prediction of subsequent total crash involvement is assessed by the aforementioned backward elimination test utilizing the likelihood ratio statistic. The results of the backward elimination tests indicate that eliminating either one or both of the two-way age by prior driving record interactions resulted in a statistically significant ($p < .01$) loss in model fit or prediction accuracy. Therefore, the interaction model which best fits these data is one containing both the age by prior total crash interaction and the age by prior total citations interaction.

The statistical significance of the interactions indicates that the relationship between prior total crashes and subsequent total crashes and between prior total citations and subsequent total crashes was not the same for the different age categories. To visualize and gain insight into the effect of these interactions on the magnitude and shape of the subsequent total crash risk curves, it is necessary to produce plots of the curves by application of the appropriate main effect and interaction product terms in the equation.

Figure 7 illustrates the subsequent 3-year total log odds of total crash involvement by prior 3-year total crashes and driver age. Figure 8 illustrates the subsequent 3-year total log odds of crash involvement by prior 3-year total citations and driver age. A constant of 4 has been added to the original log odds values in order to eliminate negative log values and, thereby, ease reader interpretation. The direction and magnitude of the interactions are consistent with the results presented in an earlier report by Gebers and Peck (1992).

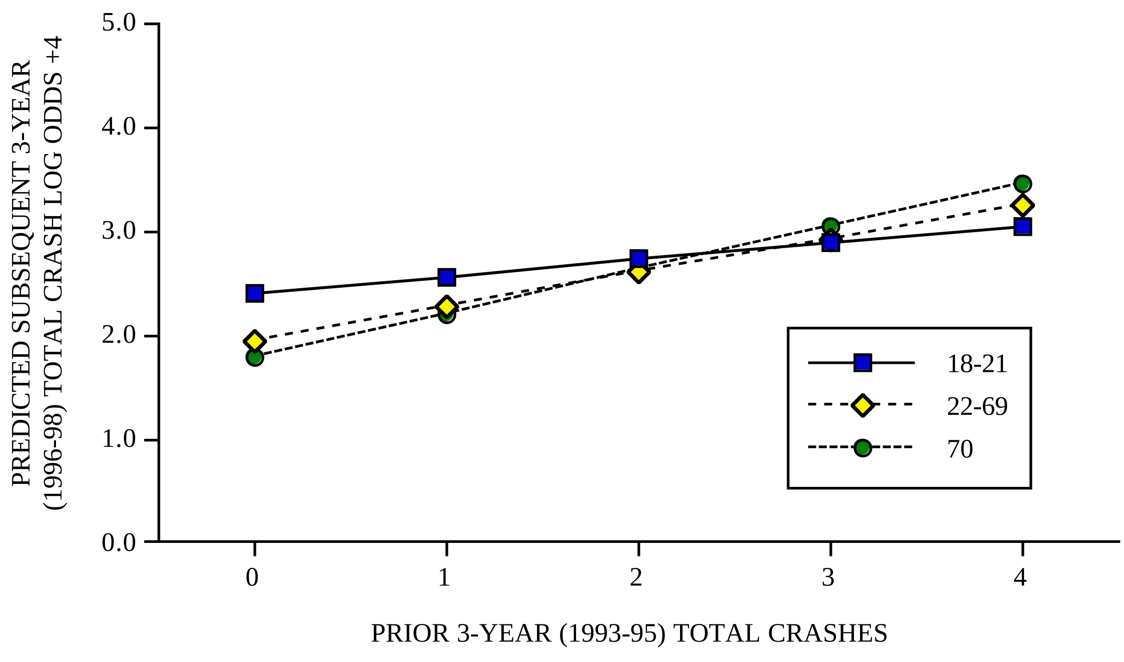


Figure 7. Predicted subsequent 3-year (1996-98) total crash log odds +4 by age group and number of prior 3-year (1993-95) total crashes.

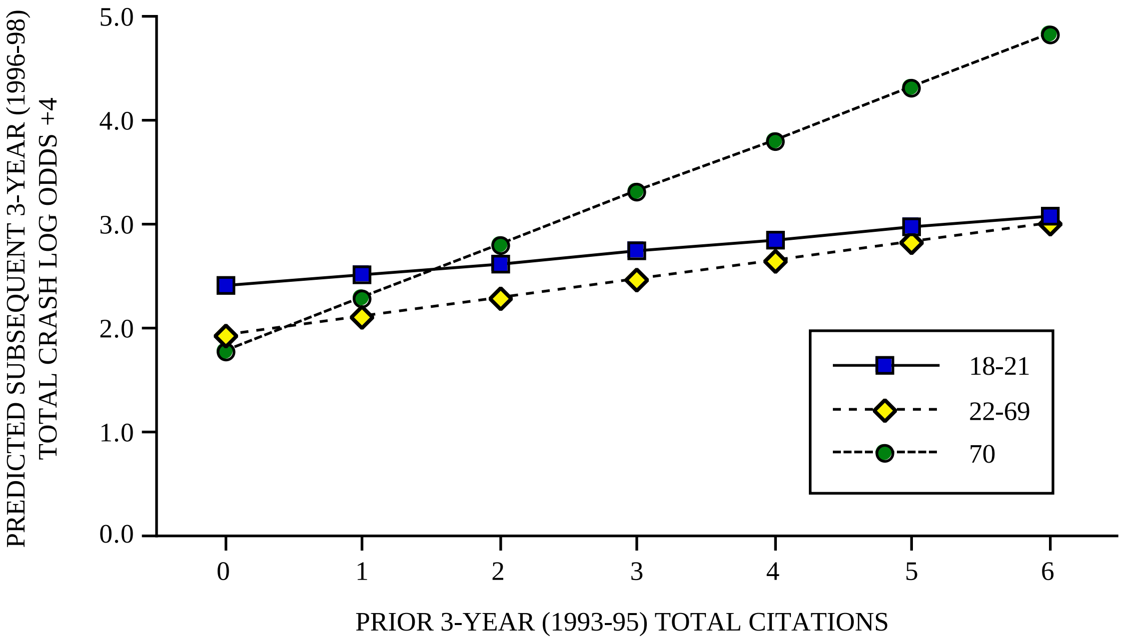


Figure 8. Predicted subsequent 3-year (1996-98) total crash log odds +4 by age group and number of prior 3-year (1993-95) total citations.

As Figure 7 shows, the odds of subsequent total crash involvement for drivers aged 18-21 exceed the odds of subsequent total crash involvement for drivers aged 22-69 and for drivers aged 70 and above through about two prior total crash involvements, and the odds for the three groups are fairly similar at three and four prior total-crash involvements.

The age by prior total citations interaction illustrated in Figure 8 indicates that through four prior total citations, drivers aged 18-21 have an odds of subsequent total crash involvement consistently higher than the odds of subsequent total crash involvement for drivers aged 22-69. At zero through two prior total citations, the odds of subsequent total crash involvement for drivers aged 18-21 are higher or approximately equal to the odds of subsequent total crash involvement for drivers 70 and above.

Figure 8 indicates that the odds of subsequent total crash involvement for drivers aged 70 and above are lower or approximately equal to drivers aged 22-69 through about one prior total citation. However, at around the two prior total citations level, the odds of subsequent total crash involvement for drivers aged 70 and above exceed the odds of subsequent total crash involvement for drivers aged 18-21 and for drivers aged 22-69.

In a subsequent section of this report, the log odds illustrated in Figures 7 and 8 will be converted to expected probabilities of subsequent total crash involvement for young and older drivers with differing counts of prior driver record incidents. The expected crash involvement probabilities associated with the age and prior driver record configurations will be used to assess the viability of applying age-mediated traffic safety treatments to high-risk driver groups currently not receiving any form of driver safety intervention.

Accuracy in Predicting Individual Crash Involvement

As discussed earlier in the Statistical Analyses section, the regression equations presented above must demonstrate some ability to correctly classify or discriminate between crash-involved and crash-free drivers before the equations can be used in an applied setting for identifying high-risk driver groups for possible treatments and/or license control measures. The purpose of the analyses presented in this section is to assess the classification accuracy of the equations in identifying crash-involved and crash-free drivers and to determine the precision of prediction.

Multiple logistic regression equations can be used to predict whether or not a driver will be crash-involved in a subsequent period. The two critical elements in assessing the adequacy of the prediction are a model's sensitivity and specificity. Sensitivity is the proportion of the event (i.e., crash-involved) outcomes that were predicted to have occurred. Specificity is the proportion of nonevent (i.e., crash-free) outcomes that were predicted to be nonevents.

A model's sensitivity and specificity rely on a single cutoff score to classify an outcome as an event or nonevent. A more complete description of classification accuracy is given by the area under the Receiver Operating Characteristic (ROC) curve. The ROC curve, originating from signal detection theory, shows how the receiver detects the existence of a signal (i.e., crash involvement) in the presence of noise. The ROC curve plots the probability of detecting true signals (sensitivity) and false signals (1-specificity) for an entire range of possible cutoffs.

The area under the ROC curve, which ranges in value from zero to one, provides a measure of the model's ability to discriminate between subjects who experience the outcome of interest versus those who do not. For example, consider a model estimating the probability (P) that a driver will become crash-involved. Suppose the interest is in predicting the outcome for each driver. One rule may be to predict that a driver will remain crash-free if P is less than .50, and predict that the driver will become crash-involved if P is greater than or equal to .50. Such a cutoff value for P may, hypothetically, for example, result in 10% sensitivity and 97% specificity. However, other cutoff scores could be used instead. For example, suppose a cutoff score of .7 were used and, hypothetically, resulted in only 3% sensitivity but 100% specificity. What becomes obvious in the two examples is that lowering the P-value cutoff to increase sensitivity reduces specificity and, alternately, increasing the cutoff score to increase specificity reduces sensitivity. What cutoff score to use is a matter of determining what type of prediction error to minimize, that is, either the false-positive rate (the proportion of predicted crash outcomes that were observed as crash-free) or the false-negative rate (the proportion of predicted no-crash outcomes that were observed as crash-involved).

If the objective is to select an optimal cutoff score for the purpose of classification, a good cutoff score to select would be one that maximizes for the model both sensitivity and specificity. Setting the cutoff score above this "optimal" level results in an increase in model specificity at the expense of reducing the model sensitivity. Setting the cutoff score below the optimal level increases model sensitivity at the expense of reducing model specificity. The determination of this optimal cutoff score, as well as other possible cutoff scores, is aided by using a graphical illustration such as the one presented in Figure 9.

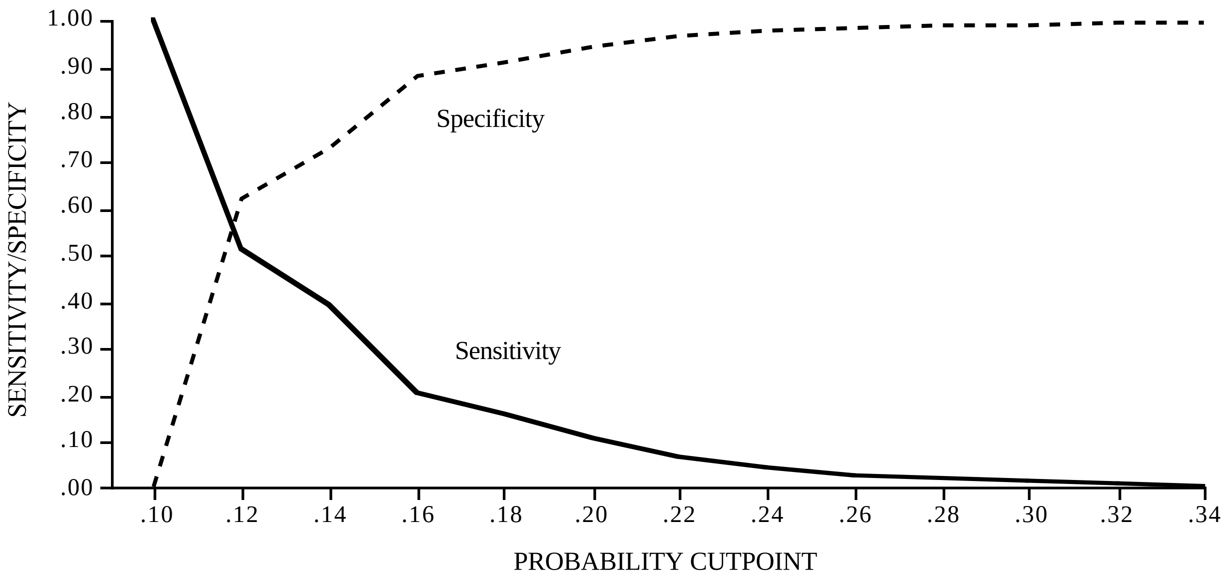


Figure 9. Plot of sensitivity and specificity versus all possible probability cutpoints for general population Model A: Regressing subsequent 3-year (1996-98) total crashes against prior 3-year (1993-95) total citations, total crashes, TVS dismissals, and FTAs.

Figure 9 plots the sensitivity and specificity values for all possible *P* cutpoints (through a value of .34) for Model A, which predicts subsequent total crash variable from prior total citations, total crashes, TVS dismissals, and FTAs. As displayed in the figure, the "optimal" choice of a cutoff for Model A would be .12 since that is approximately where the sensitivity and specificity curves intersect. Although not displayed, similar plots were also produced for Models B and C.

The classification accuracy of each selected cutoff is summarized in Table 7, which shows the number of drivers in each category. With perfect prediction, all drivers would be counted in cells a and d, and none would be counted in cells b and c. Drivers counted in cell b are false-negatives. These are drivers predicted to be crash free, but are actually crash involved. Drivers counted in cell c are false-positives, those predicted to be crash involved who are actually crash free. The desired outcome is to minimize the proportion of drivers in cells b and c and to make fewer errors than would be made in classifying drivers without the prediction equation. To be of any practical use, the equation must result in more classification accuracy than could be expected by chance alone.

Table 7

Actual Total Crash Involvement by Predicted Crash Involvement

	Actual crash status	
Predicted crash status	Crash free	Crash involved
Crash free	a (true negative)	b (false negative)
Crash involved	c (false positive)	d (true positive)

A series of classification tables were generated to illustrate the accuracy of the three regression models in predicting the future crash expectancy for individual drivers. The tables (not shown) displayed each individual's predicted and actual crash-involvement classification for each cutoff score evaluated in this study. The cutoff scores selected and evaluated in this study were the following:

- Optimal. As defined above, the optimal cutoff score represents the score where the sensitivity and specificity curves intersect. At this point, the overall predictive accuracy of the model is maximized.

- Equal marginals. This is the cutoff that produces equal actual vs. predicted marginals and approximately equal numbers of false negative and false positive predictions.

- 80% specificity. This cutoff score is defined as the score at which approximately 80% of the crash-free drivers were correctly classified. Use of the cutoff score essentially predicts crash involvement for the highest (i.e., worst) 20% of the drivers as defined by their predicted probability of subsequent crash involvement.

- 90% specificity. This cutoff score is defined as the score at which approximately 90% of the crash-free drivers were correctly classified. Use of the cutoff score essentially predicts crash involvement for the highest (i.e., worst) 10% of the drivers as defined by their predicted probability of subsequent crash involvement.

- 95% specificity. This cutoff score is defined as the score at which approximately 95% of the crash-free drivers were correctly classified. Use of the cutoff score essentially predicts crash involvement for the highest (i.e., worst) 5% of the drivers as defined by their predicted probability of subsequent crash involvement.

- 99% specificity. This cutoff score is defined as the score at which approximately 99% of the crash-free drivers were correctly classified. Use of the cutoff score essentially predicts crash involvement for the highest (i.e., worst) 1% of the drivers as defined by their predicted probability of subsequent crash involvement.

For each cutoff score defined above, the following classification measures were computed:

- Percent crash-free correctly predicted. This measure represents the model's specificity.

- Percent crash-involved correctly predicted. This measure represents the model's sensitivity.

- Percent of all drivers correctly classified. This measure represents the percent of all drivers (crash-free and crash-involved) correctly classified.

- Number of predicted positives. This measure represents the number of drivers predicted to be crash-involved.
- False-positive rate. The false-positive rate is a ratio consisting of the number of crash-free drivers incorrectly classified as crash-involved divided by the sum of all observations classified as crash-involved.

- Number of predicted negatives. This measure represents the number of drivers predicted to be crash-free.

- False-negative rate. The false-negative rate is a ratio consisting of the number of crash-involved drivers incorrectly classified as crash-free divided by the sum of all observations classified as crash free.

- Phi-coefficient. The phi-coefficient is the Pearson correlation coefficient between the actual outcome category and the predicted outcome category. As the absolute value of the coefficient increases, the degree of association between the two outcome categories becomes greater.

Tables 8-10 present the classification of individual drivers into crash-involvement categories as determined by the three regression models (A, B, & C). The probability (*P*) cutoff scores used to create the three tables are the three models' optimal cutoff scores.

Table 8

Actual Total Crash Involvement by Predicted Crash Involvement for General Population Regression Model A Using as Predictors Prior Total Citations, Total Crashes, TVS Dismissals, and FTAs (n = 187,313)

	Actual crash status		
Predicted crash status	Crash free	Crash involved	Total
Crash free	100,769 (53.80%)	12,223 (6.53%)	112,992 (60.32%)
Crash involved	61,614 (32.89%)	12,707 (6.78%)	74,321 (39.68%)
Total	162,383 (86.69%)	24,930 (13.31%)	187,313 (100%)
Percent correctly classified	62.06%	50.97%	

Note. The selected probability cut-off score maximized sensitivity and specificity. The Phi coefficient is .0904.

Table 9

Actual Total Crash Involvement by Predicted Crash Involvement for General Population Regression Model B Using as Predictors Prior Zero, One, and Two Point Citations, Total Crashes, TVS Dismissals, and FTAs (*n* = 187,313)

	Actual crash status		
Predicted crash status	Crash free	Crash involved	Total
Crash free	102,970 (54.97%)	12,507 (6.68%)	115,477 (61.65%)
Crash involved	59,413 (31.72%)	12,423 (6.63%)	71,836 (38.35%)
Total	162,383 (86.69%)	24,930 (13.31%)	187,313 (100%)
Percent correctly classified	63.41%	49.83%	

Note. The selected probability cut-off score maximized sensitivity and specificity. The Phi coefficient is .0925.

Table 10

Actual Total Crash Involvement by Predicted Crash Involvement for General Population Regression Model C Using as Predictors Prior Total Citations, Total Crashes, Age, Age by Prior Total Citations, and Age by Prior Total Crashes (*n* = 186,258)

	Actual crash status		
Predicted crash status	Crash free	Crash involved	Total
Crash free	96,299 (51.70%)	11,355 (6.10%)	107,654 (57.80%)
Crash involved	65,244 (35.03%)	13,360 (7.17%)	78,604 (42.20%)
Total	161,543 (86.73%)	24,715 (13.27%)	186,258 (100%)
Percent correctly classified	59.61%	54.06%	

Note. The selected probability cut-off score maximized sensitivity and specificity. The Phi coefficient is .0939.

Using Table 8 as an example, the optimal cutoff score computed from Model A using the predictors prior total citations, total crashes, TVS dismissals, and FTA violations correctly classified 60.58% [(100,769+12,707)/187,313] of all drivers. The model's specificity was 62.06% (100,769/162,383); the model's sensitivity was 50.97% (12,707/24,930). Use of the optimal cutoff score identified 74,321 drivers as predicted positives (i.e., predicted to be crash-involved); however, 61,614 of these drivers were incorrectly predicted to be crash-involved, yielding a false-positive rate of 82.90% (61,614/74,321). A total of 112,992 drivers were identified as predicted negatives (i.e., predicted to be crash-free); however, 12,223 of these drivers were incorrectly predicted to be crash-free (i.e., were actually crash-involved), yielding a false-negative rate of 10.82% (12,223/112,992). While the phi-coefficient of .0904 is statistically significant, indicating a true (nonchance) association between observed and predicted crash involvement outcomes, the small size of the phi-coefficient is reflective of the high false-positive rate of 82.90% associated with using the optimal cutoff score for creating the classification table.

As demonstrated in Table 9, the classification measures produced from the optimal cutoff for Model B are similar to the classification measures from Model A (using its optimal cutoff score). For example, the optimal cutoff for Model B, using as predictors prior zero-, one-, and two-point citations, total crashes, TVS dismissals, and FTA violations, correctly predicted 61.60% [(102,970+12,423)/187,313] of all drivers. Using the optimal cutoff score for Model B resulted in a specificity value of 63.41% (102,970/162,383) and a sensitivity value of 49.83% (12,423/24,930). The false-positive rate was 82.71% (59,413/71,836), and the false-negative rate was 10.83% (12,507/115,477). The phi-coefficient of .0925 for Model B is slightly larger than the phi-coefficient of .0904 associated with Model A.

Table 10 displays the classification measures associated with Model C, which used the interactions between age and prior crashes and citations. Use of the interaction equation for Model C produced classification measures slightly different from the two main-effect models A and B. For example, use of the optimal cutoff for Model C yielded the lowest specificity rate, 59.61% (96,299/161,543), but the highest sensitivity rate, 54.06% (13,360/24,715), of the three models. The false-positive rate of 83.00% (65,244/78,604) was slightly higher than the false-positive rates of 82.90% and 82.71% for Models A and B, respectively. The false-negative rate of 10.55% (11,355/107,654) for Model C was slightly lower than the false-negative rates of 10.82% and 10.83% for Models A and B, respectively. Inclusion of interaction terms in Model C and use of the models' optimal cutoff score resulted in a phi-coefficient of .0939, which was significantly higher than the phi-coefficients of .0904 and .0925 for Models A and B, respectively.

As noted above, the optimal prediction-cutoff scores used to create Tables 8-10 were selected to maximize the joint or combined sensitivity and specificity of the respective models. Recall that the optimal cutpoint is where the sensitivity and specificity curves cross. However, there are situations in which one type of prediction error may be more important than the other. In these situations, the use of different prediction-cutoff scores is warranted. If the goal is to minimize the proportion of crash-free drivers who are incorrectly predicted to have crashes (false-positives), then a higher cutoff score should be used to make it less likely for a driver to be predicted to be crash-involved by the model. Conversely, if the goal is to minimize the proportion of crash involved drivers who are erroneously predicted to be crash-free (false-negatives), then a lower cutoff score should be used to increase the probability that a driver would be classified as crash-involved. However, these two types of errors (false-positives and false-negatives) are reciprocally related. That is, if the cutoff score is lowered to reduce the rate of false-negatives, then the rate of false-positives is increased, and vice versa.

These concepts are illustrated in Table 11, which presents the classification measures for each model using each of the six cutoff scores defined above.

The results in Table 11 can be used to assess the effects of lowering or increasing a model's cutoff prediction threshold.

For example, a comparison of Model A's classification measures using a cutoff score that yielded 99% specificity to those from using a cutoff score that yielded 80% specificity illustrates the effect of lowering the cutoff prediction threshold. At 80% specificity, there is a reduction in false-negatives (11.67% versus 13.13% at 99% specificity) and a notable increase in false-positives (80.75% versus 70.58% at 99% specificity). Perhaps more notably, in lowering the cutoff score in Model A to one that obtains 80% specificity, a much greater number (31.21% at 80% vs. 2.37% at 99%) of crash-involved drivers are correctly classified (true positives). The use of a cutpoint that achieves .80 specificity also results in a much larger overall predictive accuracy than the .99 cutpoint as evidenced by their respective phi coefficients (.092 vs. .049). In fact, models that fixes specificity at .80 produced phi coefficents that were virtually identical to that of the optimum cutpoint models.

Table 11 further indicates that, as was the case with the optimal cutoff score, the three regression models yielded closely similar classification measures within each of the other cutoff scores. For example, consider the classification measures of Models A, B, and C at the cutoff score that produced equal marginals. As defined earlier, the equal marginal cutoff score produces approximately equal numbers of false-negative and false-positive predictions, as would be expected from the equality of the marginal distributions. At the marginal cutoff score, the percentage of all drivers correctly classified ranged from 79.02% for Model B to 79.23% for Model C. Specificity ranged from 87.92% for Model B to 88.19% for Model C, and sensitivity ranged from 20.65% for Model C to 21.10% for Model B. The false-positive rate ranged from 78.86% for Model B to 78.92% for Model A, and the false-negative rate ranged from 12.10% for Model C to 12.14% for Model A. The relationship between observed and predicted outcomes was relatively consistent across the three models as evidenced by the phi-coefficients, which ranged from .0887 for Model A to .0902 for Model B.

Table 11

Accuracy in Predicting 3-Year Total Crash Involvement for the General Population from Regression Equations for Models A, B and C

Cutpoint Classification measure	Model A	Model B	Model C
Number of total drivers	187,313	187,313	186,258
% of all drivers crash-free	86.69	86.69	86.73
% of all drivers crash-involved	13.31	13.31	13.27
<u>Optimal</u>			
% crash-free correctly predicted (specificity)	62.06	63.41	59.61
% crash-involved correctly predicted (sensitivity)	50.97	49.83	54.06
% of all drivers correctly classified	60.58	61.60	58.87
Number of predicted positives	74,321	71,836	78,604
False-positive rate (%)	82.90	82.71	83.00
Number of predicted negatives	112,992	115,477	107,654
False-negative rate (%)	10.82	10.83	10.55
Phi	.0904*	.0925*	.0939*
<u>Equal marginals</u>			
% crash-free correctly predicted (specificity)	88.11	87.92	88.19
% crash-involved correctly predicted (sensitivity)	20.69	21.10	20.65
% of all drivers correctly classified	79.13	79.02	79.23
Number of predicted positives	24,472	24,882	24,188
False-positive rate (%)	78.92	78.86	78.90
Number of predicted negatives	162,841	162,431	162,070
False-negative rate (%)	12.14	12.11	12.10
Phi	.0887*	.0902*	.0892*
<u>80% specificity</u>			
% crash-free correctly predicted (specificity)	80.00	80.00	80.00
% crash-involved correctly predicted (sensitivity)	31.21	30.17	30.77
% of all drivers correctly classified	73.42	74.11	73.88
Number of predicted positives	40,424	38,600	39,137
False-positive rate	80.75	80.52	80.57
Number of predicted negatives	146,889	148,713	147,121
False-negative rate (%)	11.67	11.71	11.63
Phi	.0917*	.0926*	.0937*
<u>90% specificity</u>			
% crash-free correctly predicted (specificity)	90.00	90.00	90.00
% crash-involved correctly predicted (sensitivity)	16.23	17.99	17.00
% of all drivers correctly classified	81.20	80.62	80.93
Number of predicted positives	18,370	20,346	19,200
False-positive rate (%)	77.97	77.96	78.11
Number of predicted negatives	168,943	166,967	167,058
False-negative rate (%)	12.36	12.25	12.28
Phi	.0846*	.0897*	.0861*
<u>95% specificity</u>			
% crash-free correctly predicted (specificity)	95.00	95.00	95.00
% crash-involved correctly predicted (sensitivity)	10.94	9.05	9.56
% of all drivers correctly classified	83.34	84.26	84.01
Number of predicted positives	11,733	9,073	9,793
False positive rate	76.75	75.12	75.88
Number of predicted negatives	175,580	178,240	176,465
False negative rate (%)	12.64	12.72	12.67
Phi	.0757*	.0768*	.0753*
<u>99% specificity</u>			
% crash-free correctly predicted (specificity)	99.00	99.00	99.00
% crash-involved correctly predicted (sensitivity)	2.37	2.24	2.39
% of all drivers correctly classified	86.25	86.28	86.21
Number of predicted positives	2,009	1,896	2,155
False-positive rate (%)	70.58	70.52	72.58
Number of predicted negatives	185,304	185,417	184,103
False-negative rate (%)	13.13	13.14	13.10
Phi	.0494*	.0481*	.0451*

Since any proposed traffic safety programs or treatments emanating from the regression equation approach would be applied to only those drivers who are predicted to be crash-involved (the predicted-positives), the issues of false-negative/false-positive tradeoffs and selection of cutoff thresholds have obvious implications. It was demonstrated above that the accuracy of the prediction models greatly exceed chance expectations and that it is possible to increase specificity of the crash predictions by altering the cutoff value used to classify drivers into the crash free and crash involved prediction categories. For example, using a higher cutoff threshold resulted in greater model specificity in that those predicted to be crash free were more accurately classified (lower false-positive rate). However, it was demonstrated that there was a corresponding reciprocal decrease in model sensitivity. That is, the total proportion of crash involvements correctly predicted was diminished (higher false-negative rate).

Gebers and Peck (in press) note that which type of error to minimize involves a consideration of the relative costs or disutility of the two errors. Is it, for example, more serious not to take action against a driver who will become crash involved than it is to impose a driver control action on a driver who would have remained crash-free in absence of the action? Gebers and Peck state that to some extent the answer would depend upon the nature of the driver control action taken. If the actions were relatively non obtrusive, such as warning letters or informational material, a licensing agency would probably be less concerned with false-positive errors. However, expensive countermeasures or obtrusive actions like license revocation might require a low to moderate false-positive error rate.

It is instructive at this point to consider how the department implicitly weighs these trade-offs by considering the thresholds at which license control actions are currently taken in California. Drivers defined as "negligent" in accord with the *prima facie* definition of the California Vehicle Code represent about 0.90% of the driving population and have a subsequent 1-year total crash rate that is roughly 3.5 times higher than the rate for point-free drivers. These negligent operators are subjected to driver control actions, including license suspension. Thus, the department frequently suspends traffic conviction and crash repeaters whose point count exceeds 99% of those of all drivers. If this criterion were applied to the models developed above, a cutoff score would be selected for predicting crash involvement that would be exceeded by only 1% of all drivers (i.e., the worst 1% or the 99% specificity cutoff score). More specifically, the use of a 99th percentile cutoff score would achieve, as demonstrated above, a respectable degree of specificity (low false-positive rate) but at the cost of greatly reduced sensitivity (high false-negative rate).

The following section considers the implications of the preceding results in more detail and establishes the thresholds for applying traffic safety programs and treatments to the predicted positives identified by the regression modeling approach.

Determining Thresholds for Applying Traffic Safety Interventions

As stated earlier, a major goal of the present study was to identify high-risk drivers who are not currently subjected to any form of license control or rehabilitative action and then to suggest what new or existing intervention strategies should be administered. To achieve this goal, it was necessary to establish crash-risk thresholds in order to determine what crash involvement risk is acceptable and at what point the department should intervene to reduce the crash risk of a group of drivers. As defined in the statistical analyses section, the strategy employed in this study assumes that any group of drivers whose total crash expectancy is approximately equal to or exceeds that of drivers treated by the department's negligent-operator treatment system, or that of drivers receiving one or more major violations, is a legitimate target group for licensing actions. The groups assessed for potential eligibility to receive some form of traffic safety treatment were those drivers who in the above section were predicted by the regression models to be crash involved, that is, the predicted positives.

It was stated earlier that three subgroups of NOTS drivers were used as a base for comparison with the risk prediction accuracy of the regression based models. The selection of these drivers was based on the 12-, 24-, and 36-month neg-op point criteria established by the department for the purpose of applying administratively-issued (i.e., under the regulatory authority of the driver licensing administration) postlicense control measures. The first group consisted of those drivers likely to have received a warning letter as the result of accruing two points in 12 months, four points in 24 months, or six points in 36 months. The second group consisted of drivers likely to have received a notice of intent to suspend the license by accumulating three points in 12 months, five points in 24 months, or seven points in 36 months. The third group of drivers represent drivers receiving the more severe neg-op treatment system sanctions consisting of license probation, suspension, and/or revocation as a result of accruing four or more points in 12 months, six or more points in 24 months, or eight or more points in 36 months.

The second base of comparison was a group of drivers receiving one or more two-point citations as the result of committing a major violation (e.g., DUI, hit-and-run, or speed contest). These major violators represent drivers convicted of the most serious traffic related offenses and are typically sanctioned directly through the courts.

Table 12 presents the sample sizes and the observed 3-year total crash rates for the three NOTS-points driver subgroups, drivers with one or more major (two-point) violations, and each model's predicted positives for the six cutoff scores utilized for the analyses.

Table 12

3-Year Total Crash Rate by Driver Selection Criteria

Selection criteria	*n*	3-year total crashes/100 drivers
2/4/6 NOTS points	5,229	23.47
3/5/7 NOTS points	1,224	24.59
4+/6+/8+ NOTS points	856	27.34
1 or more major (2-point) violations	4,785	25.29
Optimal cutoff		
Model A predicted positives	74,321	19.75
Model B predicted positives	71,836	19.99
Model C predicted positives	78,604	19.58
Equal marginals cutoff		
Model A predicted positives	24,472	25.18
Model B predicted positives	24,882	25.22
Model C predicted positives	24,188	25.23
80% specificity cutoff		
Model A predicted positives	40,424	22.56
Model B predicted positives	38,600	22.85
Model C predicted positives	39,137	22.84
90% specificity cutoff		
Model A predicted positives	18,370	26.41
Model B predicted positives	20,346	26.42
Model C predicted positives	19,200	26.30
95% specificity cutoff		
Model A predicted positives	11,733	28.16
Model B predicted positives	9,073	30.21
Model C predicted positives	9,793	29.27
99% specificity cutoff		
Model A predicted positives	2,009	37.63
Model B predicted positives	1,896	37.39
Model C predicted positives	2,155	34.85

An examination of Table 12 offers a number of interesting insights.

Consistent with expectations, there is a linear or monotonic relationship between prior neg-op points and subsequent total crashes. That is, an increase in the rate of accumulated prior points is associated with an increase in the number of subsequent total crash involvements. For example, drivers at the 2/4/6 NOTS point count level exhibit a subsequent 3-year total crash rate of approximately 23.47 crashes per 100 drivers. As drivers advance along the continuum to the 3/5/7 NOTS point count level, the subsequent 3-year total crash rate increases to 24.59 crashes per 100 drivers. Drivers accumulating the highest point count threshold, 4+/6+/8+ NOTS points, exhibit the highest subsequent 3-year total crash rate of approximately 27.34 crashes per 100 drivers.

The 4,785 drivers with one or more major violations accumulate a total crash rate of approximately 25.29 crashes per 100 drivers. The reader will note that the crash rate of the major violators falls roughly between the crash range of 24.59 per 100 drivers and 27.34 per 100 drivers reported above for the 3/5/7 and 4+/6+/8+ NOTS point drivers, respectively. This outcome was expected since it is likely that a number of drivers receiving one or more major violations during a 3-year period will also accumulate the required number of points qualifying them for the higher level NOTS sanctions and, therefore, will exhibit somewhat similar rates of driver record incidents. One limitation in using these estimated crash rates as measures of intrinsic risk is that they have been attenuated by any prior treatments or interventions that some of the drivers would have received as a result of their inflated records. However, any suppression would be negligible to moderate and would not invalidate their use as risk threshold baselines.

A comparison between each model's crash rates within a specific cutoff score identifies groups of predicted positives with very similar risks of subsequent crash involvement. For example, within the cutoff score that produced 90% specificity, the observed subsequent 3-year total crash rates ranged from 26.30 crashes per 100 drivers for the 19,200 predicted positives identified by Model C to 26.42 crashes per 100 drivers for the 20,346 predicted positives identified by Model B. This similarity in risk level was expected given the overlap between the predicted positives within a specified cutoff score. For example, within the 90% specificity cutoff score, the overlap between Models A and B was 17,376 drivers; the overlap between Models A and C was 12,711 drivers, and the overlap between Models B and C was 13,319 drivers.

The effect of altering the cutoff score to increase specificity and/or isolate the "riskiest" or worst drivers is clearly evident when one examines both the sample sizes and crash rates of the predicted positives. For example, the optimal cutoff score that maximized both model sensitivity and specificity produced the largest number of predicted positives (ranging from 71,321 to 78,604 drivers) but resulted in identifying a group of predicted positives with the lowest subsequent mean crash rates (ranging from 19.58 to 19.99 crashes per 100 drivers) among the cutoff values examined in the study. However, when the cutoff score was adjusted to increase model specificity and/or identify only the worst drivers, the model predicted fewer crash-involved drivers, but those predicted to be crash involved were much more likely to be crash involved. For example, the cutoff score that identified the worst 1% (i.e. 99% specificity cutoff score) of the drivers on the basis of their predicted probability scores produced the smallest number of predicted positives (ranging from 1,896 to 2,155 drivers), but the subsequent crash rate of the predicted groups ranged from 34.85 to 37.63 crashes per 100 drivers.

The fact that the mean crash rates of the selected groups increase with increasing specificity is a necessary consequence of greater deviancy of the identified group. Although one of the objectives is to identify maximally high risk drivers, the increased stringency greatly diminishes the number of drivers selected for treatment, thereby attenuating the potential number of crashes that can be prevented.

Of central interest in this section of the report are the comparisons of the crash rates displayed in Table 12 between the predicted positives from each cutoff score strategy and the respective NOTS subgroups and major violators. To arrive at the comparisons, it was necessary to transform the crash rates presented in Table 12 into measures of risk or risk ratios.

Figures 10 through 13 present a common way of expressing risk in terms of the risk of a base comparison group (e.g., 2/4/6 NOTS point group). To obtain the risk ratios illustrated in the four figures, the average number of subsequent total crash involvements for a particular group of predicted positives within a specific cutoff score strategy was divided by the average number of subsequent total crashes for drivers in the base comparison group, for example the 2/4/6 NOTS point drivers. By using this risk ratio or "times-as-many" relationship, the subsequent crash rate for a group of predicted positives was indexed to the crash rate of the base comparison group. The higher the relative risk ratio or times-as-many index, the greater the risk of a group of predicted positives relative to the risk of the base comparison group, which by definition has a risk ratio or times-as-many index of 1.0. For the example above, a quotient of 1.5 would indicate that the group of predicted positives identified by using a specific cutoff score had 1.5 times-as-many (or 50% more) subsequent total crash involvements as had by drivers at the 2/4/6 NOTS points threshold. Alternatively, a quotient of 0.86 would indicate that the predicted positives identified by using a specific cutoff score had about 14% (1.00 - 0.86) fewer crash involvements than did the 2/4/6 NOTS point group.

The four figures are discussed in detail below.

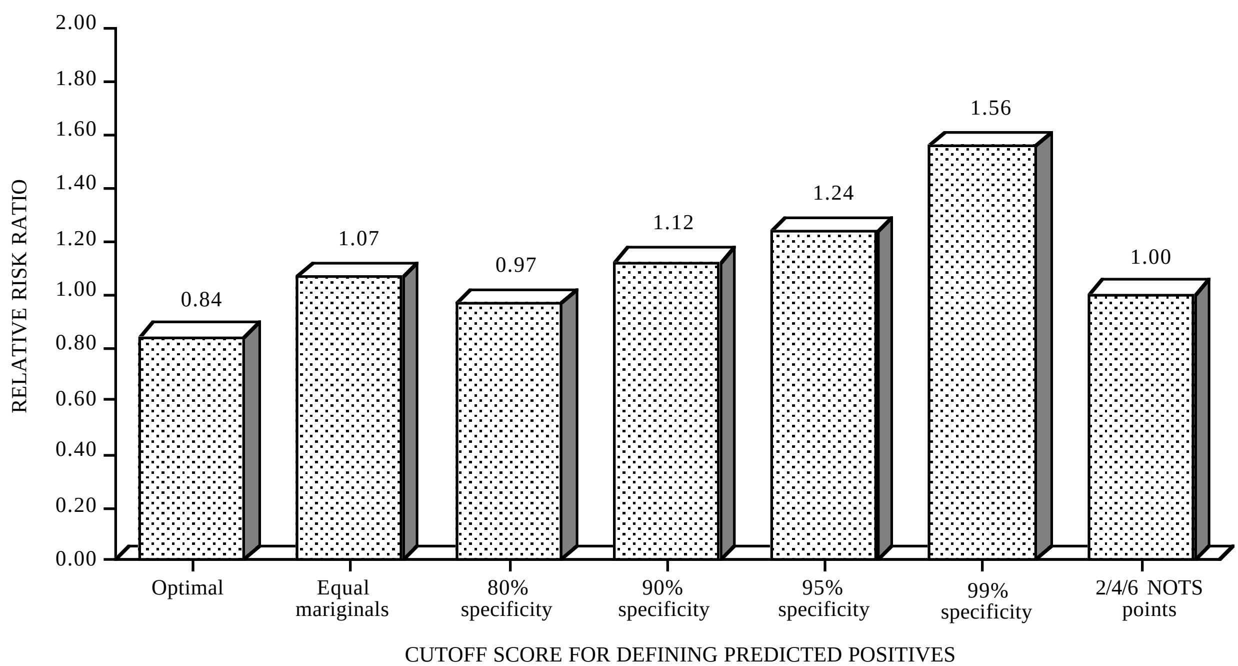


Figure 10. Three-year total crash risk ratio for predicted positives within cutoff score selection criteria relative to 2/4/6 NOTS point drivers.

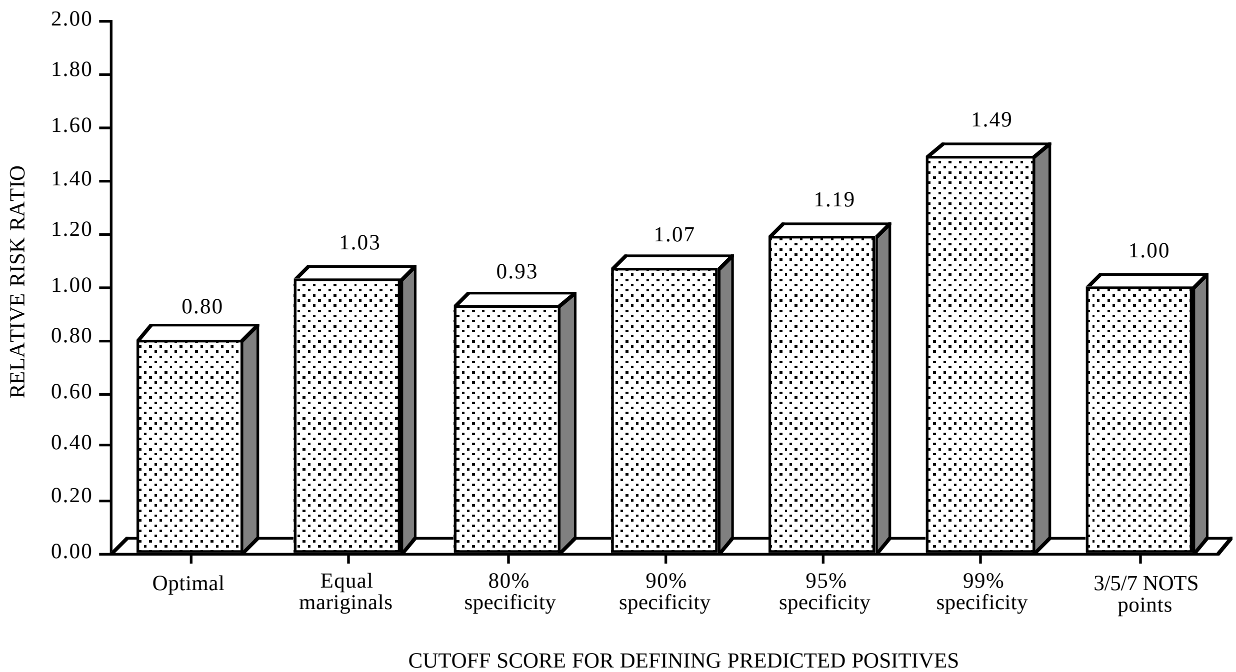


Figure 11. Three-year total crash risk ratio for predicted positives within cutoff score selection criteria relative to 3/5/7 NOTS point drivers.

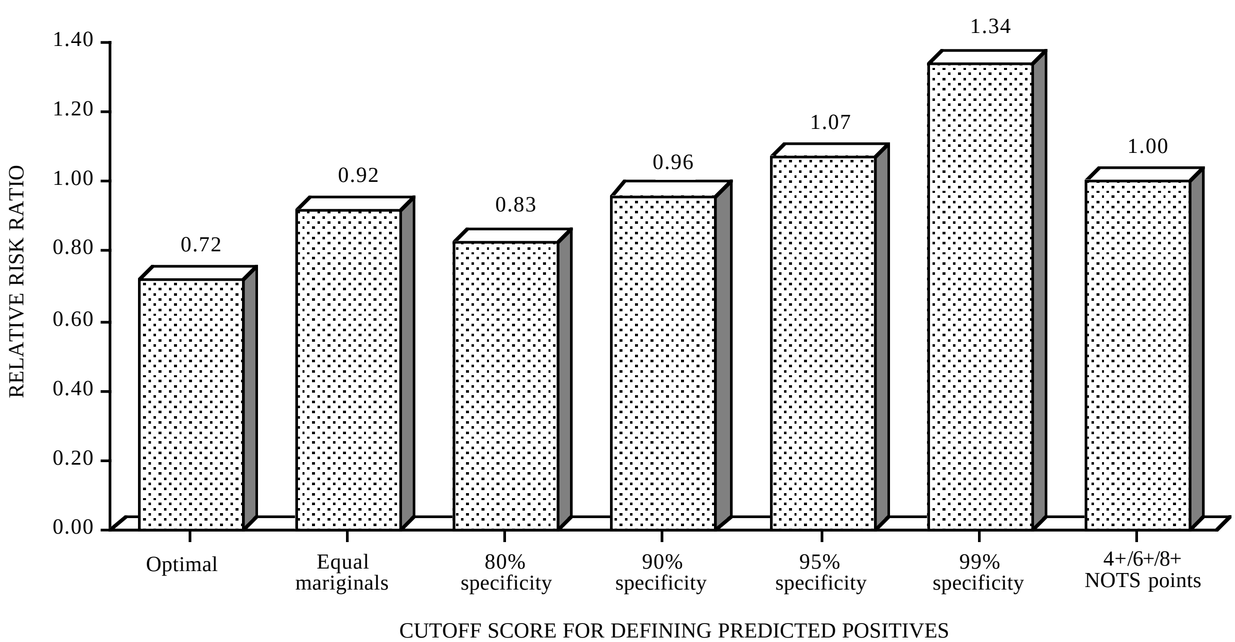


Figure 12. Three-year total crash risk ratio for predicted positives within cutoff score selection criteria relative to 4+/6+/8+ NOTS point drivers.

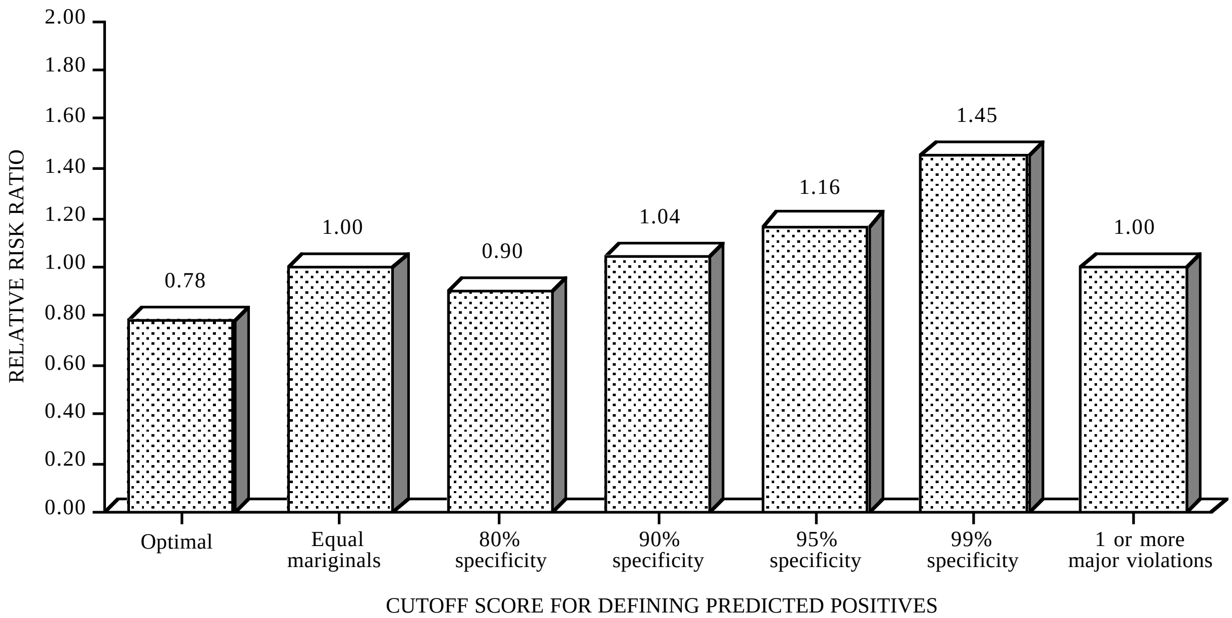


Figure 13. Three-year total crash risk ratio for predicted positives within cutoff score selection criteria relative to drivers with 1 or more major violations.

Figure 10 presents the total crash risk-ratios for the predicted positives within each cutoff score criteria relative to the 2/4/6 NOTS point drivers. An examination of the relative risk indices indicates that with the exception of predicted positives identified by the optimal and 80% specificity cutoff scores, all of the remaining predicted positive groups exceeded the crash risk of the 2/4/6 NOTS point drivers. For example, the relative risk ratios in the figure indicate the following:

- Predicted positives identified by the equal marginals cutoff score were 1.07 times as likely to be involved in a subsequent crash.
- Predicted positives identified by the 90% specificity cutoff score were 1.12 times as likely to be involved in a subsequent crash.
- Predicted positives identified by the 95% specificity cutoff score were 1.24 times as likely to be involved in a subsequent crash.
- Predicted positives identified by the 99% specificity cutoff score were 1.56 times as likely to be involved in a subsequent crash.

The results presented in Figure 11 illustrate the total crash risk ratios for the predicted positives within cutoff score criteria relative to the 3/5/7 NOTS point drivers. As was the case with the above comparisons involving the 2/4/6 NOTS point group, all the predicted positive groups except those identified by the optimal and 80% specificity cutoff scores exceeded the crash risk of the 3/5/7 NOTS point drivers. The relative risk ratios for the groups illustrated in Figure 11 indicate the following about the predicted positives relative to the sample of 3/5/7 NOTS point drivers:

- Predicted positives identified by the equal marginals cutoff score were 1.03 times as likely to be involved in a subsequent crash.
- Predicted positives identified by the 90% specificity cutoff score were 1.07 times as likely to be involved in a subsequent crash.
- Predicted positives identified by the 95% specificity cutoff score were 1.19 times as likely to be involved in a subsequent crash.
- Predicted positives identified by the 99% specificity cutoff score were 1.49 times as likely to be involved in a subsequent crash.

Figure 12 illustrates the 3-year total crash risk ratio for the predicted positives within each cutoff score criteria relative to NOTS 4+/6+/8+ point drivers. The results indicate that predicted positives in only two out of the six cutoff score selection groups exceeded the crash risk of the 4+/6+/8+ NOTS point drivers. These two groups utilize the cutoff scores that resulted in model specificity meeting or exceeding 95% and, therefore, identified as predicted positives those drivers with the highest risk (exceeding the risk of 95% or 99% of the general driving population) of subsequent crash involvement. Specifically, an examination of the relative risk ratios presented in Figure 12 yield the following conclusions:

- Predicted positives identified by the 95% specificity cutoff score were 1.07 times as likely to be involved in a subsequent crash.
- Predicted positives identified by the 99% specificity cutoff score were 1.34 times as likely to be involved in a subsequent crash.

In addition to the above, the .90 specificity and equal marginals cutoffs were almost equivalent to the NOTS criteria as evidenced by risk ratios exceeding .90.

A comparison of the 3-year total crash risk ratios for the predicted positives within cutoff score selection criteria relative to drivers with one or more major (two point) violations is presented in Figure 13. An examination of the relative risk ratios in the figure indicate that predicted positives in three of the six cutoff score groups exceeded the total crash rate of drivers with one or more major violations. Specifically, the relative risk ratios in Figure 13 offer the following conclusions:

- Predicted positives identified by the 90% specificity cutoff score were 1.04 times as likely to be crash involved.
- Predicted positives identified by the 95% specificity cutoff score were 1.16 times as likely to be crash involved.
- Predicted positives identified by the 99% specificity cutoff score were 1.45 times as likely to be crash involved.

Both the equal marginals and .80 specificity cutoffs produced risk ratios of .90 or above.

Table 13

Expected Probability of Subsequent 3-Year (1996-98) Total Crash Involvement and Estimated Number of Selected Drivers by Prior 3-Year (1993-95) Driver Record Incident Combination

Model Driver record incident combination	Expected probability of subsequent crash involvement	Estimated number of drivers with the incident combination in the prediction cutoff groups: All drivers	90% specificity	95% specificity	99% specificity
Model A					
(1) 1 total citation, 1 total crash, 1 TVS dismissal	.2337	233,000	233,000	232,700	0
(2) 2 total citations, 2 total crashes, 2 TVS dismissals	.3497	3,100	3,100	3,100	3,100
(3) 2 total citations, 2 total crashes, 1 TVS dismissal	.3320	16,400	16,400	16,400	15,300
(4) 3 total citations, 0 total crashes, 1 TVS dismissal	.2395	130,100	129,600	109,800	0
(5) 3 total citations, 0 total crashes, 2 TVS dismissals	.3182	28,900	28,900	28,900	0
(6) 3 total citations, 2 total crashes, 0 TVS dismissals	.2850	9,000	9,000	9,000	5,200
(7) 3 total citations, 2 total crashes, 1 TVS dismissal	.3715	8,200	8,200	8,200	8,100
(8) 3 total citations, 2 total crashes, 2 TVS dismissals	.4669	2,300	2,300	2,300	2,300
Model B					
(9) 1 one-point citation, 2 total crashes, 1 TVS dismissal	.3018	16,300	16,300	16,300	15,500
(10) 1 one-point citation, 1 total crash, 1 TVS dismissal	.2389	92,300	92,300	92,100	3,900
(11) 2 one-point citations, 0 total crash, 2 TVS dismissals	.2911	11,300	11,300	11,300	10,600
(12) 2 one-point citations, 1 total crash, 2 TVS dismissals	.3612	3,400	3,400	3,400	3,400
(13) 2 one-point citations, 2 total crashes, 2 TVS dismissals	.4378	800	800	800	800
(14) 1-zero point citation, 2 total crashes, 1 TVS dismissal	.2942	10,300	10,300	10,300	9,100

Table 13 (continued)

Model Driver record incident combination	Expected probability of subsequent crash involvement	Estimated number of drivers with the incident combination in the prediction cutoff groups: All drivers	90% specificity	95% specificity	99% specificity
Model B (continued)					
(15) 1-zero point citation, 2 total crashes, 2 TVS dismissals	.3789	1,200	1,200	1,200	1,200
(16) 1-zero point citation, 1-one point citation, 2 total crashes, 2 TVS dismissals	.4288	500	500	500	500
(17) 3 zero-point citations, 1 one-point citation, 2 TVS dismissals	.3579	100	100	100	100
(18) 3 zero-point citations, 1 one-point citation, 3 TVS dismissals	.4493	100	100	100	100
(19) 0 zero-point citation, 0 one-point citation, 2 TVS dismissals	.2132	73,000	72,900	72,400	4,000
(20) 0 zero-point citation, 0 one-point citation, 3 TVS dismissals	.2840	1,400	1,400	1,400	400
Model C					
(21) 18-21 years of age, 2 total crashes	.2183	30,600	30,600	30,600	9,400
(22) 70 years of age and older, 2 total crashes	.2013	12,900	12,900	4,200	4,200
(23) 18-21 years of age, 3 total crashes	.2469	3,200	3,200	3,200	1,500
(24) 70 years of age and older, 3 total crashes	.2769	1,000	1,000	1,000	1,000
(25) 18-21 years of age, 2 total citations	.2027	121,000	121,000	121,000	500
(26) 70 years of age and older, 2 total citations	.2313	13,500	13,500	13,500	3500
(27) 18-21 years of age, 3 total citations	.2216	61,200	61,200	61,200	4000
(28) 70 years of age and older, 3 total citations	.3333	2,900	2,900	2,900	2900
(29) 18-21 years of age, 4 total citations	.2418	33,400	33,400	33,400	12100
(30) 70 years of age and older, 4 total citations	.4536	400	400	400	400

In addition to identifying risk of drivers predicted to be crash-involved within various cutoff score criteria, the nature of multiple regression also allows for the application of the linear regression equations to estimate the probability of subsequent crash involvement for a group of drivers based upon knowledge of driver age and the number of incidents (e.g., crashes and/or citations) accumulated during a prior time period. The following discussion uses the regression equation parameters presented in Tables 4 through 6 to compute the estimated probabilities of subsequent total crash involvements for various counts and combinations of prior crashes, citations, TVS dismissals, and driver age. Following the computation of the estimated probabilities, risk ratios are computed for groups with the various driver record incident counts and combinations and are then compared to the probability of crash involvement associated with the three NOTS point driver groups and drivers with one or more major (two point) violations.

Table 13 presents the expected probability of subsequent 3-year (1996-95) total crash involvement and estimated number of selected drivers in the statewide population by prior 3-year (1993-95) driver record incident combination.

The entries associated with driver record incident combination 1 through 8 were computed from Model A's regression parameters presented in Table 4. As discussed in detail earlier, Model A employed a main effects model in which prior total citations and crashes, TVS citation dismissals, and FTA violations were used to predict subsequent total crashes.

As an illustration, consider from Table 13 driver record incident combination 1 associated with Model A. This driver record incident combination applies to drivers who accrue during the prior 3 years one total citation, one total crash, and one TVS dismissal. Using the regression parameters from Table 4, the logit or logs odds of subsequent total crash involvement is computed as the following:

$$\text{Logit} = -2.0691 + (0.1733 \times 1) + (0.3148 \times 1) + (0.3036 \times 1) = -1.1874$$

The corresponding expected probability of subsequent crash involvement displayed in Table 13 for drivers with this incident combination is computed by an exponential transformation of the above computed logit:

$$\text{Probability} = \exp(-1.1874) \;/\; (1 + \exp(-1.1874)) = 0.2337$$

The remaining entries in Table 13 were computed similarly.

Entries for driver record incident combinations 9 through 20 were computed from Model B's regression parameters presented earlier in Table 5. Model B was a main effects model in which prior total crashes, zero-, one-, and two-point citations, TVS dismissals, and FTA violations were used to predict subsequent total crashes.

The entries associated with driver record incident combination 21 through 30 were calculated from Model C's regression parameters discussed in detail in Table 6. Model C was an interaction effects model in which the primary focus of interest was the moderating effects between driver age and counts of prior total crashes and prior total citations on the likelihood of subsequent total crash involvement.

Recall that the major objectives of this study were to conduct a statistical analysis in order to identify sub-groups of problem drivers whose crash risk equals or exceeds that of drivers receiving the various levels of negligent operator sanctions as defined by the department's current neg-op treatment system and other possible risk-cutoff values and to develop new, or select existing, intervention strategies to use for high-risk drivers currently not subjected to any form of license control or rehabilitative action. Therefore, the selection of the specific driver record incident combinations was designed to identify groups of general population drivers whose combined prior citation and crash involvement counts do not include a major violation and are below the 12/24/36 month point threshold qualifying for membership in one of the three NOTS point driver groups. It was anticipated that the selection of the driver record incident combinations displayed in Table 13 would also identify groups of drivers whose expected probability of subsequent crash involvement would approximate or exceed that of at least one of the NOTS point driver subgroups or drivers with one or more major violations.

An examination of the entries in Table 13 yields a number of interesting observations.

For example, the group with the lowest estimated risk of subsequent crash involvement is associated with driver record incident combination number 22. This group consists of drivers who were 70 years of age and older and had two crash involvements during the prior 3-year period. The expected probability of subsequent crash involvement for this group of drivers was .201.

The group with the highest estimated risk of subsequent crash involvement is associated with driver record incident combination 8. This group was comprised of drivers who accumulated a count of three total citations, two total crashes, and two TVS dismissals during the prior 3 years. The expected probability of subsequent crash involvement for this group was .467.

The table entries indicate that increases in the number of TVS dismissals, while holding the remaining driver record incident counts constant, are associated with notable increases in the expected probability of future crash involvement. For example, consider driver record incident combinations 6 and 7. Both scenarios identify groups of drivers with three prior citations and two prior crashes. The difference between the two groups is the count of prior TVS dismissals. Driver record incident combination 6, which captures drivers with no TVS dismissals, results in a subsequent probability of crash involvement of .285. However, driver record incident combination 7, which captures drivers with one TVS dismissal, results in a subsequent probability of crash involvement of .372. The difference between .372 and .285 represents an increased crash probability of approximately 31%. The association between TVS diversion and significantly increased crash risk has been documented in prior California research (e.g., Peck & Gebers, 1991).

If no interaction existed between age and prior driving record, one would expect that the relationship between prior driving record incidents and subsequent crash involvement would be the same at each age level. One would also expect that within any level of prior crashes or citations older drivers would have a lower estimated probability of subsequent crash involvement relative to younger drivers. However, evidence that age interacts with traffic citation and crash record is evident when examining the estimated crash probabilities associated with driver record incident combinations 21 through 30.

For example, an examination of driver record incident combination 21 indicates that drivers 18-21 years of age with two prior total crashes had an estimated probability of subsequent crash involvement of .218, while driver record incident combination 22 indicates that drivers 70 years of age and older with two prior total crashes had an estimated probability of subsequent crash involvement of .201. The difference between these two probability values represents an increased crash expectancy of 8.5% for drivers 18-21 years of age. On the other hand, the pattern reverses when the number of crashes is increased from two to three crashes. That is, drivers 18-21 years of age with three prior total crashes (driver record incident combination 23) have an estimated probability of subsequent crash involvement of .247. However, driver record incident combination 24 indicates that drivers aged 70 years and above with three prior total crashes exhibit an estimated probability of subsequent crash involvement of .277. The difference between these two probability values represents an increased crash expectancy of 12% for drivers aged 70 and above.

A similar pattern emerges among counts of prior citations. For example, an examination of driver record incident combination 25 indicates that drivers 18-21 years of age with two prior total citations exhibit an estimated probability of subsequent crash involvement of .203, while driver record incident combination 26 indicates that drivers 70 years of age and older with two prior total citations exhibit an estimated probability of subsequent crash involvement of .231. The difference between these two probability values represents an increased crash expectancy of 14% for drivers 70 years of age and above. Note that this difference widens when the number of citations is increased from two to three citations. That is, drivers 18-21 years of age with three prior total citations (driver record combination 27) have an estimated probability of subsequent crash involvement of .222. Driver record incident combination 28 indicates that drivers aged 70 years and above with three prior total citations exhibit an estimated probability of subsequent crash involvement of .333. The difference between these two probability values represents an increased crash expectancy of 50% for drivers aged 70 and above. Similar age by prior record interactions were observed in a prior study by Gebers and Peck (1992).

In Table 13, the entries under the heading entitled *estimated number of drivers with the incident combination in the prediction cutoff groups* represent an estimated 1-year's volume of statewide drivers expected to accumulate the various driver record incident criteria. The volumes are provided for all drivers in the general driving population and for the three cutoff score selection criteria that produced groups of predicted positives with the highest crash rates and relative risk estimates as presented in Table 12 and Figures 10 through 13. The estimated volumes are intended to assist in any decision making process identifying which high-risk driver groups to target for possible license control actions.

Note, for example, driver record incident combination 10. This combination selects drivers with one one-point citation, one total crash, and one TVS dismissal and is associated with an estimated subsequent crash probability of .239. If the department decided to target with some traffic safety interventions all drivers in the general population with this particular driver record configuration, it is estimated that approximately 92,300 drivers would be eligible for the intervention. However, if the department decided to concentrate on the predicted positives identified with the 99% specificity cutoff score, the number would be reduced to approximately 3,900. The reason for the reduction in the volume of identified predicted positive drivers is because the predicted positives for the model take into account the other variables in the model in addition to the specified driver record incident combination to arrive at the predicted score. Therefore, the observed crash expectancy of the predicted positives using the 99% specificity cutoff score would be much higher than, for example, all general population drivers with the same driver record incident combination.

The reader will also note that several of the combinations do not identify any drivers in the general population who were in the group of predictive positives the model selected at the extreme end of the risk continuum. For example, driver record incident combination 4 consists of drivers with three prior total citations, no total crashes, and one TVS dismissal. Drivers with this driver record configuration have an expected subsequent total crash probability of .2395. It is estimated that approximately 130,100 statewide drivers accumulate this configuration. If the department decided to target with some traffic safety intervention the predicted positives identified by the 95% specificity cutoff score, the number of drivers would drop by only 20,300 to a total of 109,800. No drivers with this particular driver record incident combination were identified in the worst 1% (i.e., 99% specificity) of the drivers predicted by the model.

The trade-offs involving the volume of drivers targeted for treatment by the various models and driver record incident combinations in relation to benefit and cost factors will be discussed in detail in a subsequent section of this report.

In a manner analogous to the relative risk ratios presented earlier for the predicted positives identified through the use of the various prediction cutoff score criteria, the expected relative risk ratios of 3-year total crash involvement for the 28 driver record incident combinations, presented in Table 13 were computed. The expected relative risk ratios for the various combinations are displayed in Table 14. The ratios were computed by exponentiating the respective regression equation parameter estimates from Tables 4 through 6 to derive estimated probabilities for each driver record combination. The resultant estimated probabilities were divided by the probability of crash involvement for each of the NOTS points driver groups and the major violators groups to obtain the estimates of relative risk presented in the table.

Table 14

Relative Risk of 3-Year Total Crash Involvement Compared to NOTS Point and Major (2-Point) Violation Groups by Driver Record Incident Combination

Model Driver record incident combination	NOTS point count and major violation status 2/4/6 NOTS points	3/5/7 NOTS points	4+/6+/8+ NOTS points	1 or more major (2 point) violations
Model A				
(1) 1 total citation, 1 total crash, 1 TVS dismissal	1.19	1.14	0.85	1.11
(2) 2 total citations, 2 total crashes, 2 TVS dismissals	1.79	1.70	1.28	1.66
(3) 2 total citations, 2 total crashes, 1 TVS dismissal	1.70	1.61	1.21	1.58
(4) 3 total citations, 0 total crashes, 1 TVS dismissal	1.22	1.16	0.88	1.14
(5) 3 total citations, 0 total crashes, 2 TVS dismissals	1.63	1.55	1.16	1.51
(6) 3 total citations, 2 total crashes, 0 TVS dismissals	1.46	1.38	1.04	1.35
(7) 3 total citations, 2 total crashes, 1 TVS dismissal	1.90	1.80	1.36	1.76
(8) 3 total citations, 2 total crashes, 2 TVS dismissals	2.39	2.27	1.71	2.22
Model B				
(9) 1 one-point citation, 2 total crashes, 1 TVS dismissal	1.54	1.47	1.10	1.43
(10) 1 one-point citation, 1 total crash, 1 TVS dismissal	1.22	1.16	0.87	1.13
(11) 2 one-point citations, 0 total crash, 2 TVS dismissals	1.49	1.41	1.06	1.38
(12) 2 one-point citations, 1 total crash, 2 TVS dismissals	1.85	1.75	1.32	1.71
(13) 2 one-point citations, 2 total crashes, 2 TVS dismissals	2.24	2.13	1.60	2.08
(14) 1-zero point citation, 2 total crashes, 1 TVS dismissal	1.50	1.43	1.08	1.40
(15) 1-zero point citation, 2 total crashes, 2 TVS dismissals	1.94	1.84	1.39	1.80

Table 14 (Continued)

Model Driver record incident combination	2/4/6 NOTS points	3/5/7 NOTS points	4+/6+/8+ NOTS points	1 or more major (2 point) violations
	NOTS point count and major violation status			
Model B (cont.)				
(16) 1-zero point citation, 1-one point citation, 2 total crashes, 2 TVS dismissals	2.19	2.08	1.57	2.04
(17) 3 zero-point citations, 1 one-point citation, 2 TVS dismissals	1.83	1.74	1.31	1.70
(18) 3 zero-point citation, 1 one-point citation, 2 TVS dismissals	2.30	2.18	1.64	2.13
(19) 0 zero-point citation, 0 one-point citation, 2 TVS dismissals	1.09	1.04	0.78	1.01
(20) 0 zero-point citations, 0 one-point citation, 3 TVS dismissals	1.45	1.38	1.04	1.35
Model C				
(21) 18-21 years of age, 2 total crashes	1.12	1.06	0.80	1.04
(22) 70 years of age and older, 2 total crashes	1.03	0.98	0.74	0.96
(23) 18-21 years of age, 3 total crashes	1.26	1.20	0.90	1.17
(24) 70 years of age and older, 3 total crashes	1.42	1.34	1.01	1.31
(25) 18-21 years of age, 2 total citations	1.04	0.98	0.74	0.96
(26) 70 years of age and older, 2 total citations	1.18	1.12	0.85	1.10
(27) 18-21 years of age, 3 total citations	1.13	1.08	0.81	1.05
(28) 70 years of age and older, 3 total citations	1.70	1.62	1.22	1.58
(29) 18-21 years of age, 4 total citations	1.24	1.17	0.88	1.15
(30) 70 years of age and older, 4 total citations	2.32	2.20	1.66	2.15

Note that in the majority of instances, the relative risk of subsequent crash involvement for each group identified by the driver record combinations clearly exceeds the relative risk of crash involvement of the three NOTS point driver groups and of major violators. For example, driver record combination 2 consisted of drivers who during the prior 3-year period accumulated two total citations, two total crashes, and two TVS citation dismissals. The relative risk of subsequent crash involvement for this driver record combination exceeded the crash risk of the four base comparison groups. That is, drivers with this particular combination of prior incident counts have an expected relative crash risk that is 1.79 times higher than the 2/4/6 NOTS point drivers, 1.70 times higher than the 3/5/7 NOTS point drivers, 1.28 times higher than the 4+/6+/8+ NOTS point drivers, and 1.66 times higher than major violators.

An examination of the driver record combination produced from main effects Model A (combinations 1-8) indicates that driver record combination 8 was associated with the highest relative risk of subsequent crash involvement. This group consisted of drivers accumulating three prior total citations, two total crashes, and two TVS dismissals. This driver record combination identified a group of drivers whose expected relative crash risk is 2.39 times higher than the 2/4/6 NOTS point drivers, 2.27 times higher than the 3/5/7 NOTS point drivers, 1.71 times higher than the 4+/6+/8+ NOTS point drivers, and 2.22 times higher than major violators.

Among the driver record combination groups identified by main effects Model B (driver record combinations 9 through 20), driver record combination 18 identified the group with the highest relative risk. This driver record combination consisted of drivers who accumulated during the prior 3-year period three zero-point citations, one one-point citation, and three TVS dismissals. The relative risk measures associated with this driver record combination identified a group of drivers whose subsequent crash risk is 2.30 times higher than the 2/4/6 NOTS point drivers, 2.18 times higher than the 3/5/7 NOTS point drivers, 1.64 times higher than the 4+/6+/8+ NOTS point drivers, and 2.13 times higher than major violators.

Within the driver record incident combinations (combination numbers 21-30) associated with interaction Model C, the driver record combination associated with the highest relative risk was combination 30. This group consisted of drivers who are 70 years of age and older and who accumulated four prior total citations. These drivers exhibited a relative risk of subsequent total crash involvement 2.32 times higher than the 2/4/6 NOTS point drivers, 2.20 times higher than the 3/5/7 NOTS point drivers, 1.66 times higher than the 4+/6+/8+ NOTS point drivers, and 2.15 times higher than the major violators.

The above analyses provide substantiation that driver selection strategies utilizing the regression equations approach are able to identify groups of "untreated" drivers whose crash risk exceeds the risk of drivers eligible to receive administrative license control measures as a result of accumulating neg-op points and also the risk of drivers eligible to receive court related sanctions as a result of a major (mostly alcohol-related) violations. Each identified group could conceivably be the target of a traffic safety program treatment. However, given the limited monetary resources available to a driver licensing agency, cost considerations are very relevant in the decision making process. The following section presents a discussion of cost and benefit considerations.

Cost-Benefit and Cost-Factors of Traffic Safety Intervention Programs
All seven driver identification systems compared in the above section (i.e., Models A, B, and C, NOTS point drivers 2/4/6, 3/5/7, and 4+/6+/+8+, and major [2-point] violators) are examples of specific countermeasure problem identification systems. One or more risk groups were identified under each scenario. Theoretically, each identified group could be targeted with a traffic safety program treatment that is designed to reduce group crash involvement. However, as briefly referenced in the preceding paragraph, from a traffic safety administrator's perspective, there is typically a fixed amount of monetary and personnel resources available to develop and implement traffic safety programs. Therefore, the question becomes how to most effectively use the available resources.

To illustrate the application of a benefit-cost strategy in traffic safety program design and decision making, it is assumed that both the cost and the value of doing nothing at all is zero. That is, if there is no program implementation, there are no associated benefits or costs. Since any program would be applied only to drivers predicted to be crash involved (the predicted positives), all benefits and costs would be derived from this group of drivers. For drivers predicted to be crash free, no program will be applied. The number of drivers to be targeted is dependent on the cost of the traffic safety intervention and on the available resources. The more expensive the program, the fewer the number of drivers that can be treated.

All benefits obtained from any traffic safety program are considered here to be in the form of crash reduction; the costs are the costs of administering the program. Each driver predicted to be crash involved would trigger the cost of the program treatment. The benefits are limited to crash prediction (and prevention) in the true-positive group (i.e., drivers correctly predicted to be crash involved during a subsequent period of time). There is obviously no way to distinguish in advance between true positives and false positives. If one were able to determine true-positives and false-positives in advance, perfect prediction would exist. Since perfect prediction is not possible, the mean crash rate for the predicted positives is used in computing benefits, even though the benefits are confined to the true-positive classification. That is, the benefits can only be derived from the true positives since this is the group of drivers who were actually involved in one or more subsequent crashes. No program is capable of preventing crashes that were never destined to occur. On the other hand, program costs must be based on all of the predicted positives. A treatment program must be applied to all of the predicted positives on the basis of the prediction or selection criteria. It is, therefore, inevitable that many of the treated drivers would not be crash involved even if the treatment program were not applied.

The methodology presented in the following discussion of benefits and costs is replicative of the methodology presented in Kadell and Peck (1979) and in McConnell and Hagen (1980), who presented a series of benefit and cost demonstrations under a series of hypothetical scenarios. The benefits of costs are computed as the following:

- Benefits = average crash rate for predicted positives x percent crash reduction/100 x cost of each crash x number of predicted positives

- Cost = unit cost of each traffic safety program application x number of predicted positives

- Net program value or benefits = benefits minus costs

The net benefit cost improvements from regression Model A under a variety of hypothetical treatment effects and program cost scenarios relative to the predicted positives at the 80% specificity cutoff score were computed. The results are presented in Table 15.

Table 15

Net Benefits Gain from Using Regression Model A Under Various Hypothetical Treatment Effects and Program Costs for the Predicted Positives at the 80% Specificity Cutoff Score

Unit program cost	Intervention level and effect size								
	2/4/6			3/5/7			4+/6+/8+		
	1%	4%	7%	1%	4%	7%	1%	4%	7%
$5.00	$16,605,201	$119,213,304	$221,821,407	$18,613,718	$133,254,874	$247,896,029	$18,720,742	$134,234,966	$249,749,191
$25.00	-$53,784,799	$48,823,304	$151,431,407	-$59,786,281	$54,854,974	$169,496,029	-$60,415,258	$55,098,966	$170,613,191
$100.00	-$317,747,299	-$215,139,196	-$112,531,093	-$353,786,281	-$239,145,126	-$124,503,971	-$357,175,258	-$241,661,034	-$126,146,809

Note. A conservative cost estimate, provided by Peck and Healey (1995-96), of $13,000 per crash is used in calculating the net benefit gains.

The monetary entries in the table represent the net benefits difference between the predicted positives identified by using the 80% specificity cutoff score and the three NOTS intervention levels. The net benefits differences are provided for 1%, 4%, and 7% hypothetical treatment effect sizes and unit program costs of $5.00, $25.00, and $100.00.

The positive direction of the vast majority of the entries associated with the unit program costs of $5.00 and $25.00 favors the regression approach over that of the intervention levels based on NOTS point counts. The negative entries, most notably for the most expensive unit program cost of $100.00, represent a negative benefit-cost index. In these instances, costs exceeded benefits for both the regression and NOTS intervention levels and, therefore, would represent an ineffective countermeasure to implement. However this ineffective scenarios could be altered dramatically by increasing specificity from .80 to, say, .95. For example, using a .95 specificity cutpoint would result in positive benefit-outcome for the majority of the scenarios illustrated in Table 15.

Another way to examine the safety impact of using the regression approach and .80 specificity level is simply the calculate the additional number of crashes that would be prevented under various scenarios.

Table 16

Estimated Crash Reduction Under Various Hypothetical Treatment Effects and Intervention Levels

Intervention level	Number of drivers	Estimated number of crashes without intervention	Estimated number of crashes prevented if treated with an intervention that reduced crashes by		
			1%	4%	7%
2/4/6	522,900	24,000	240	960	1,680
3/5/7	122,400	5,900	60	240	400
4+/6+/8+	85,600	4,600	50	180	320
Predicted positives using 80% specificity cutoff score	4,042,400	179,000	1,800	7,200	12,500

Note: The number of crashes has been adjusted to account for an estimated average of 1.7 involvements (drivers) per crash (Kuan & Marsh, 1981).

The values in the table reflect the superiority of targeting drivers based on the regression approach.

For example, the 4+/6+/8+ NOTS level identifies an estimated 85,600 drivers. The estimated number of crashes for this group with no intervention is approximately 4,600. Assume that the department applies a countermeasure to this group that will prevent 4,600 x .04 ≅ 180 crashes, representing a crash reduction of about 4%. However, use of the predicted positives using the 80% specificity cutoff scores identifies 4,042,400 drivers. Application of a countermeasure that reduces the number of crashes for this group by the same value of 4% prevents an estimated 179,000 x .04 ≅ 7,200 crashes.

The reader needs to be clearly aware that these figures apply only to a hypothetical demonstration. A true benefits-cost analysis is only possible when the true traffic safety intervention unit costs, treatment effects sizes, and accident costs are known. However, the above illustration does demonstrate the potential safety benefits of the regression approach under a variety of scenarios.

RESOURCE ALLOCATION AND OPTIMIZATION USING THE REGRESSION MODEL APPROACH

If the department decides to incorporate the regression model approach to identify high-risk drivers currently escaping traffic safety interventions, the development and implementation of the traffic safety intervention resource allocation plan can take a number of forms.

One possible form that would be very compatible with the current hierarchical structure of the NOTS program would be the implementation of multiple cutoff scores. This approach would involve indicating how many drivers a program would treat within any given year. The lowest cutoff score obtained from the regression equation would be set at a particular value so that a specific number or percentage of drivers would exceed the defined cutoff score. For example, in each model presented in the Results section of this report, cutoff scores were selected to identify the worst 1% (i.e., the 99% specificity cutoff score) of the driving population based upon their estimated probabilities of subsequent crash involvement. Targeting 1% of the total driving population would involve an administrative decision guided by the available resources. Since California's current NOTS program involves four hierarchical levels of more severe and expensive interventions (warning letters, notice of intent to suspend, probation/suspension, and probation violator sanctions), the adoption of a regression equation approach would need to incorporate a series of cutoff scores. Each higher cutoff score in the series would be specified to identify a treatment population volume compatible with resources available for a specific level of intervention. Therefore, the smallest group of drivers would be identified by use of the highest cutoff score and the highest predicted risk of subsequent crash involvement. This group of drivers would receive the most severe and possibly most expensive treatment. Drivers with lower expected levels of risk of subsequent crash involvement would have lower cutoff scores and would form the larger groups exposed to the less restrictive and possibly less expensive interventions. Obviously, any number of cutoff scores can be specified in response to the desired number of driver groups to be treated. The use of the regression equation strategy to identify high-risk drivers provides the flexibility to be responsive to any desired format or refinement of a driver improvement program.

An alternative form for a regression based identification system would be the use of only one predicted risk cutoff score. This strategy would be appropriate under the scenario in which only limited resources are available to treat a small proportion of the driving population. For example, a traffic safety administrator may decide to treat only drivers who pose the highest estimated risk of subsequent crash involvement with a more expensive and intensive crash prevention countermeasure. The cutoff score could be set (e.g., to obtain 99% specificity or the worst 1% of drivers) to select the desired number of drivers for application of the crash countermeasure intervention.

The benefit cost illustrations demonstrated some potential benefits of using a .80 specificity level since this level of specificity was close to optimal in terms of net predictive power and sensitivity. However, it produces a volume of drivers that might be operationally infeasible irrespective of public safety and benefit-cost considerations.

Whatever approach is adopted, development of countermeasure strategies requires examination of the defining characteristics of the risk groups that have a risk ratio in excess of 1.0 (Table 14). Recall that these represent offenders whose crash risk exceeds the crash rate for offenders who currently receive some form of departmental driver improvement action. In the next section, we outline some initial steps and considerations toward developing appropriate countermeasure strategies.

DEVELOPMENT OF COUNTERMEASURE STRATEGIES

Although none of the models perform well in predicting which individual drivers will become crash-involved, the models do identify and define groups of drivers who present substantially increased risks of having crashes during a subsequent 3-year time window. More importantly, the models have greater predictive power than the present negligent operator point system, and they identify substantial numbers of high crash-risk drivers whose records show no evidence of having received driver improvement or license control interventions. Some illustrative benefit-cost calculations indicated that even very inexpensive and marginally effective interventions, such as warning letters and informational brochures, offer substantial cost-effective crash reduction potential.

In examining the defining characteristics of the high-risk groups that currently escape driver improvement interventions, the majority are characterized by either TVS dismissals, citations, or crashes. These elements often combine with each other and with other risk factors to increase crash risk beyond that of drivers who meet the state's *prima facie* definition of a "negligent operator."

An effective countermeasure system presupposes the existence of treatments or interventions that reduce negligent driving behavior and, fortunately, there exists a large body of scientific literature documenting a number of effective programs. However, there are two more fundamental considerations in constructing a countermeasure system: (1) the countermeasures must be economically and operationally feasible, and (2) it must be legally permissible. For these reasons, we will only consider here interventions that involve minimal expense, no in-person contact with DMV personnel, and no license-control actions. With the above constraints in mind, we offer the following menu of interventions.

<u>Crash-Triggered Treatments</u>
Any high-risk group characterized by two or more crashes would receive an educational brochure on crash-avoidance combined with a self-study/self-test kit, as described and evaluated in Helander (1983). This treatment reduced subsequent crash rate by 23% and was highly cost-effective. Authority for intervening against drivers based on their crash history, irrespective of culpability, can be found in CVC Section 13800a.

<u>Traffic Violator School-Triggered Treatment</u>
Offenders would be sent a customized soft warning letter upon the second TVS citation dismissal or any combination of TVS and other entries equaling three. For TVS and other entry combinations of four or more, a customized hard letter would be used. Authorization for initiating driver improvement actions against offenders based on a non-conviction citation (TVS) is contained in CVC Section 13800(d), 12809(e), and 13359.

<u>Age-Mediated Risk Group Treatments</u>
Offenders whose high-risk designation is partially attributed to youth (18-21) would receive a customized warning letter and informational brochure. Those whose high-risk is mediated by old age (70 & older) would receive a home-study self-assessment kit as recommended in Gebers and Peck (1992). This effort is currently under experimental evaluation by DMV's Research and Development Branch.

<u>Other Risk Groups</u>
Several of the high-risk groups are not characterized by either TVS or crash entries. In most cases, these "other" groups have multiple zero-point citations that, when combined with other entries, elevate their crash-risk to that of negligent operator status. Although it may be counterintuitive, the fact that "noncountable" traffic

citations are predictive of increased crash risk has been documented in numerous California studies (e.g., Gebers, 1999; Peck & Gebers, 1992). Initiating punitive license control actions against offenders on the basis of noncountable citations would not be appropriate, but there is nothing that would prohibit use of advisory letters warning such drivers of crash risks and of the negative consequences of continued violations.

The above four strategies provide a general framework for linking each high-risk target group to a cost-effective and operationally feasible countermeasure. As noted previously, the volume of additional interventions can be controlled by altering the cutoff threshold to achieve the desired volume and level of specificity. Recall that prediction curves were generated for four levels of specificity: .80, .90, .95, and .99. The relative risk values shown in Table 14 are based on a cut-point that optimizes overall predictive accuracy rather than one that fixes specificity at a high level. It is possible to increase the relative-risk ratios in Table 14 to correspond to higher specificities. As demonstrated in the Results section, increasing specificity results in larger relative risk indices and reduced volumes of targeted drivers. Unfortunately, there is a price to pay for an increased emphasis on specificity: The sensitivity of the models in identifying crash-involved drivers (true positives) is reduced, which lessens the net number of crashes that are potentially preventable by the intervention system. An important advantage of the countermeasures proposed above is that they do not subject the driver to license control actions or other punitive and obtrusive requirements. As such, concern over specificity (not initiating a treatment against drivers who were not crash-involved) is greatly lessened in deference to the objective of increased sensitivity and enhanced public safety.

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